

A Systems Approach for Understanding Cell Signaling

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What is a “Systems Approach” in the Context of Biological Organisms?

- ▶ Looking at cells as integrated systems and not as mere collections of parts
- ▶ Seeks to understand how changes in any given component will affect the behavior of the entire system
- ▶ Requires integration of information from molecular biology, biochemistry, physics and genetics to understand relationship between different sets of scientific data.
- ▶ Goal is a “Higher order” understanding of life processes.

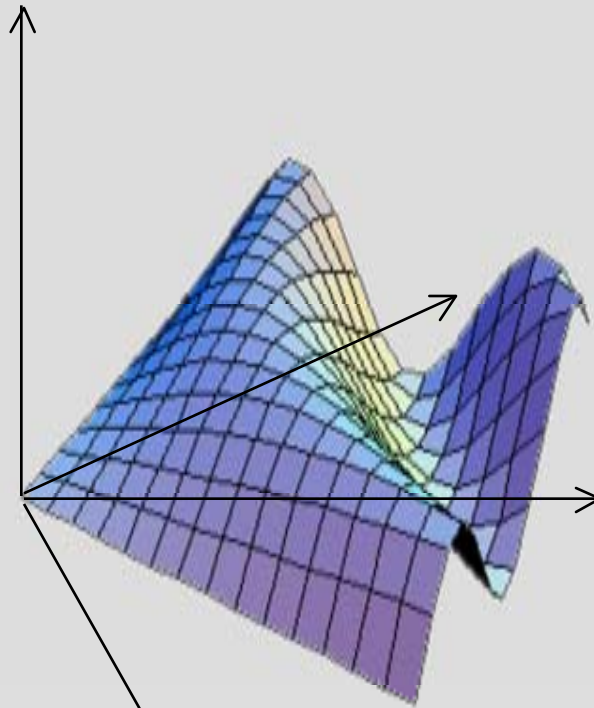
Systems Perspective

Cell function:

death,
proliferation,
differentiation,
migration, ...

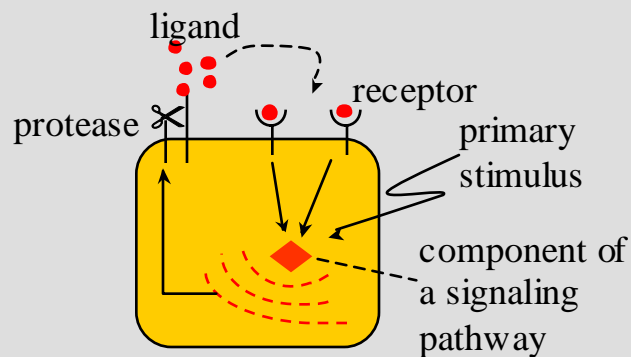
Molecular parameters:

protein levels / states /
locations / interactions /
activities



Ultimate aim:
*Understanding
and
prediction
of effects of
component
properties*

Currently, individual Investigators work on a small part of a larger problem

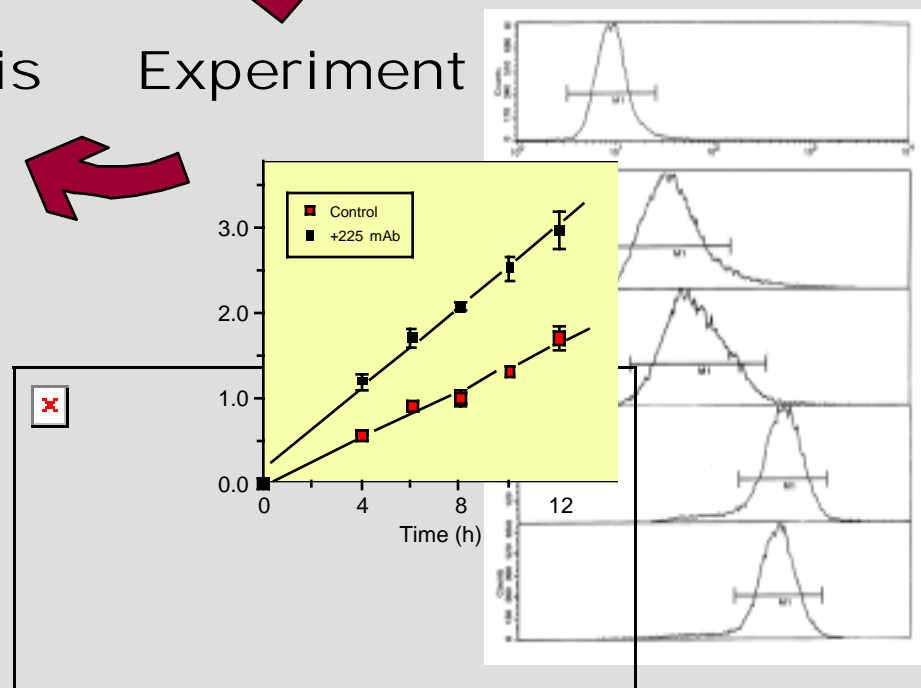


Theory

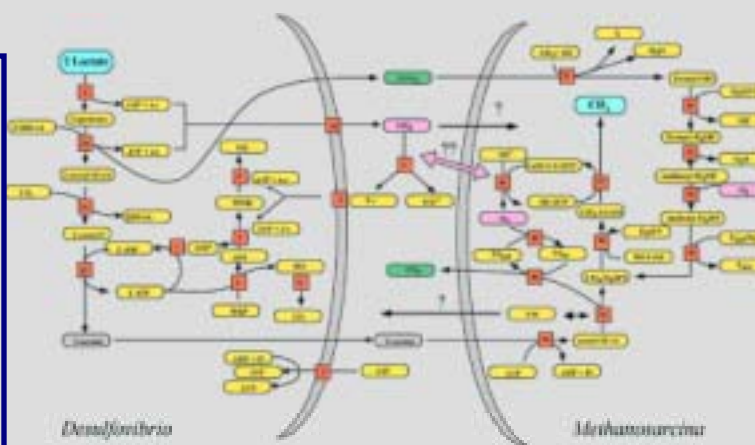
Analysis

Experiment

| Cell line | EGFR | HER2 |
|-----------------------|----------------------|----------------------|
| Parental (184A1 HMEC) | $\sim 2 \times 10^5$ | $\sim 2 \times 10^4$ |
| HER2 clone 29L | $\sim 2 \times 10^5$ | $\sim 1 \times 10^5$ |
| HER2 clone 12 | $\sim 2 \times 10^5$ | $\sim 2 \times 10^5$ |
| HER2 clone 24H | $\sim 2 \times 10^5$ | $\sim 8 \times 10^5$ |
| HER2 clone 1 | $\sim 2 \times 10^5$ | $\sim 8 \times 10^5$ |



To understand organisms from a “systems perspective,” it is necessary to integrate a large quantity of information



Metabolic and regulatory models

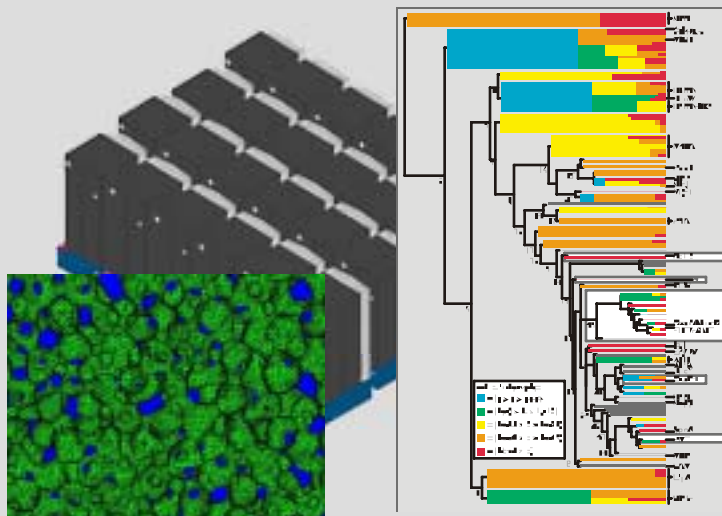
Advanced Computation and Information Management

Theory

Analysis

Experiment

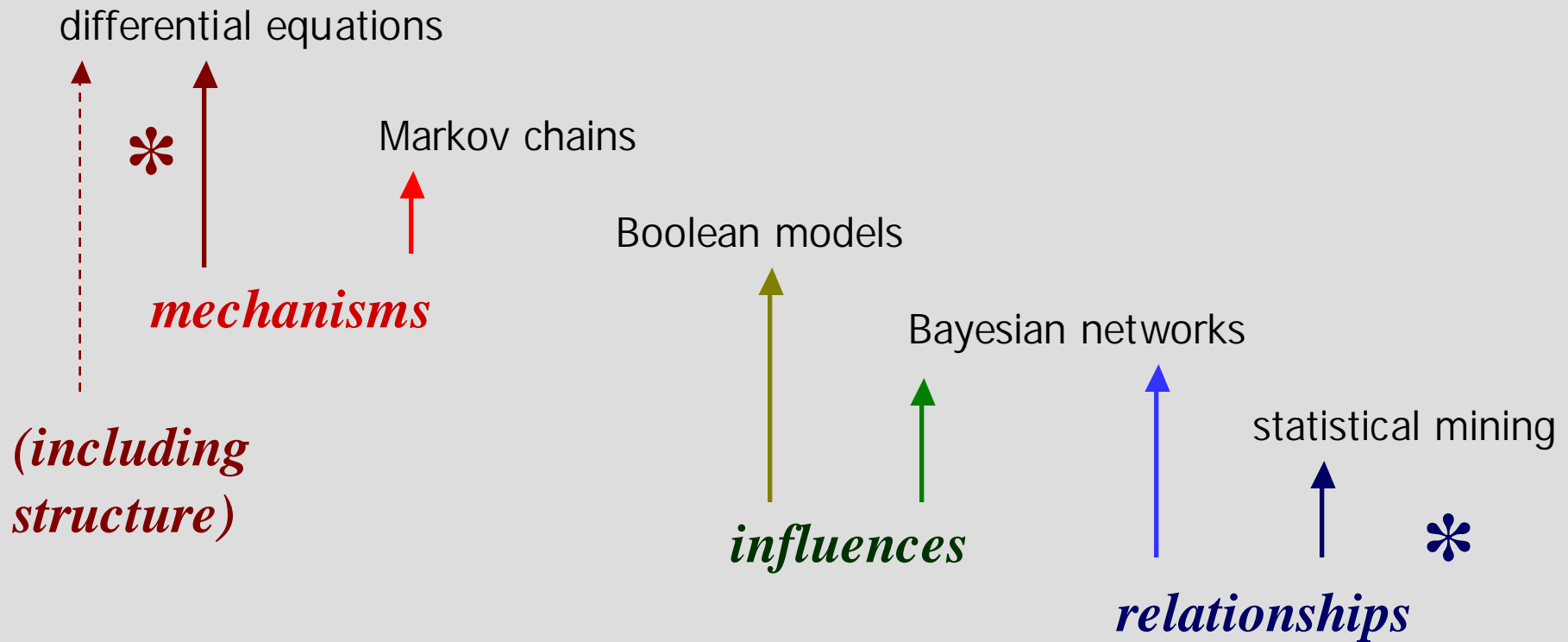
Advanced High-Throughput Technologies



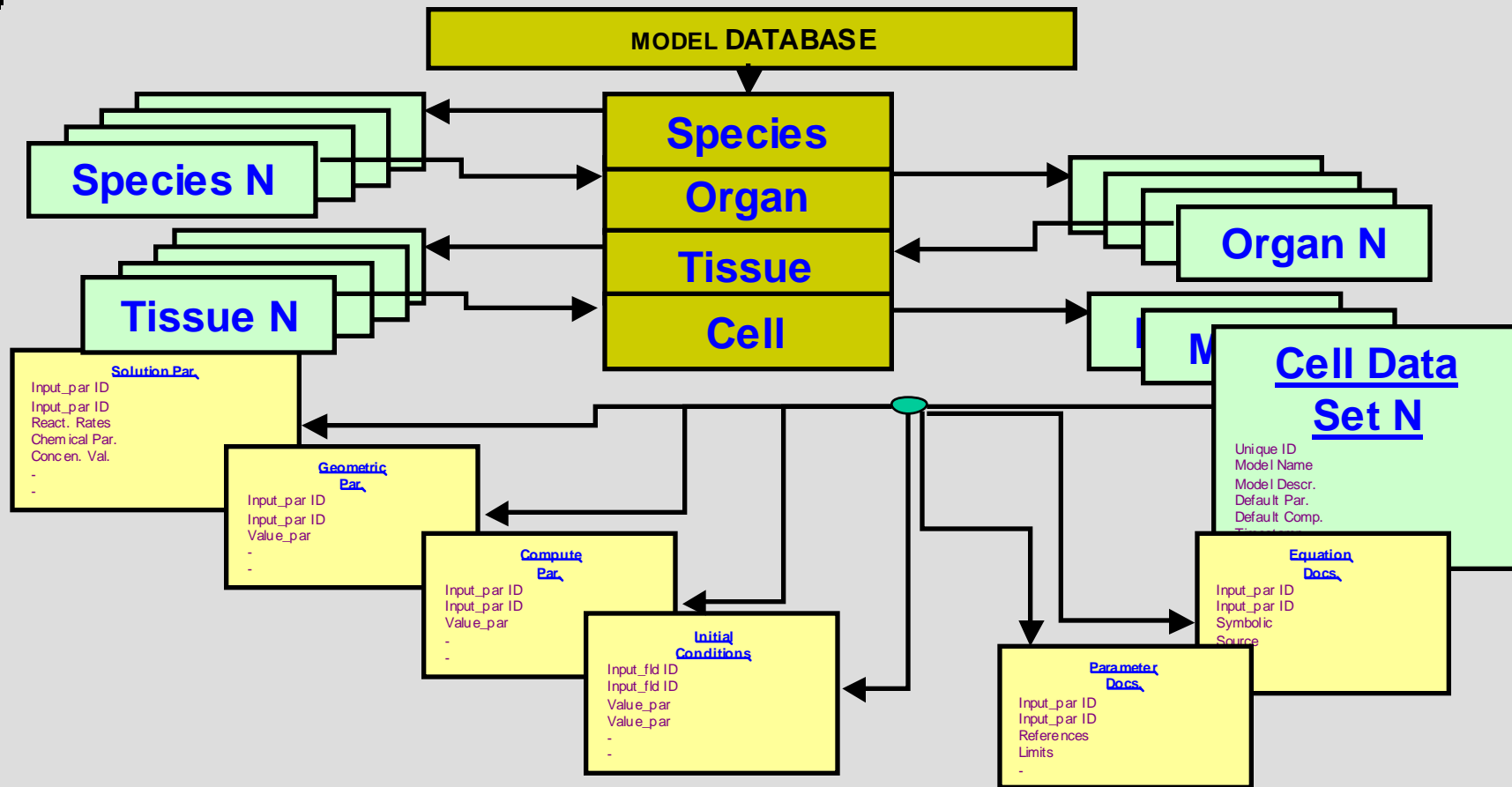
Computational Modeling Approaches -- Diverse Spectrum

SPECIFIED

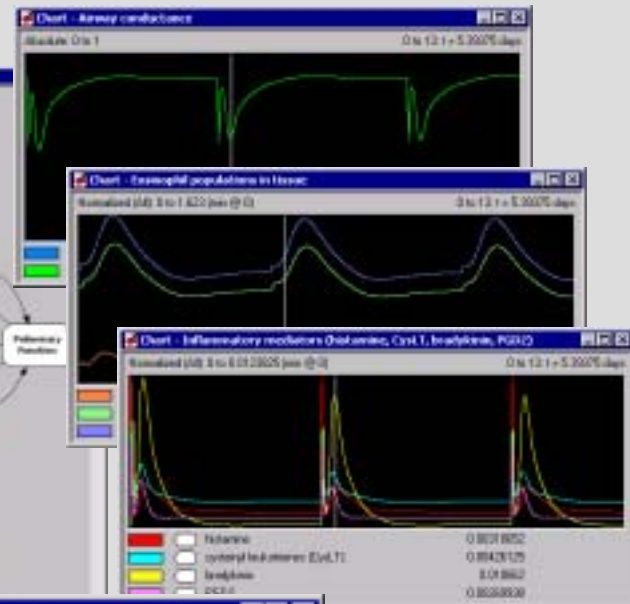
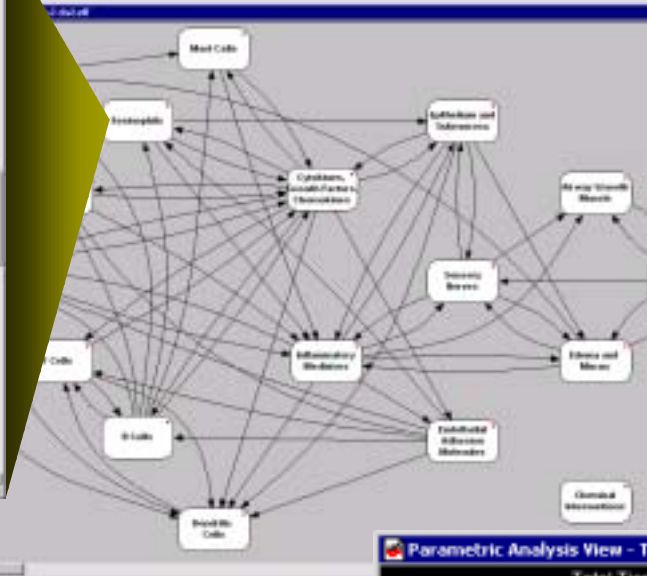
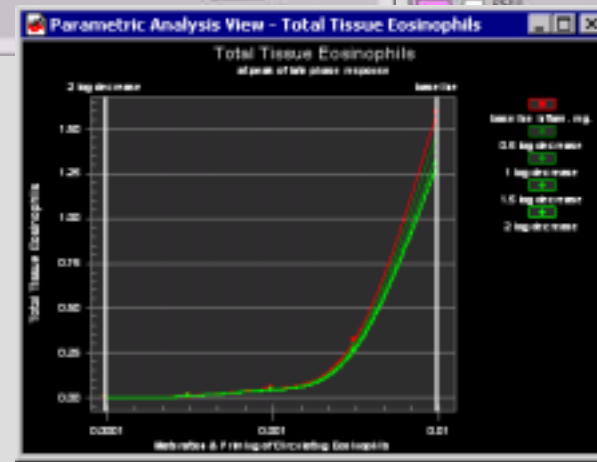
ABSTRACTED



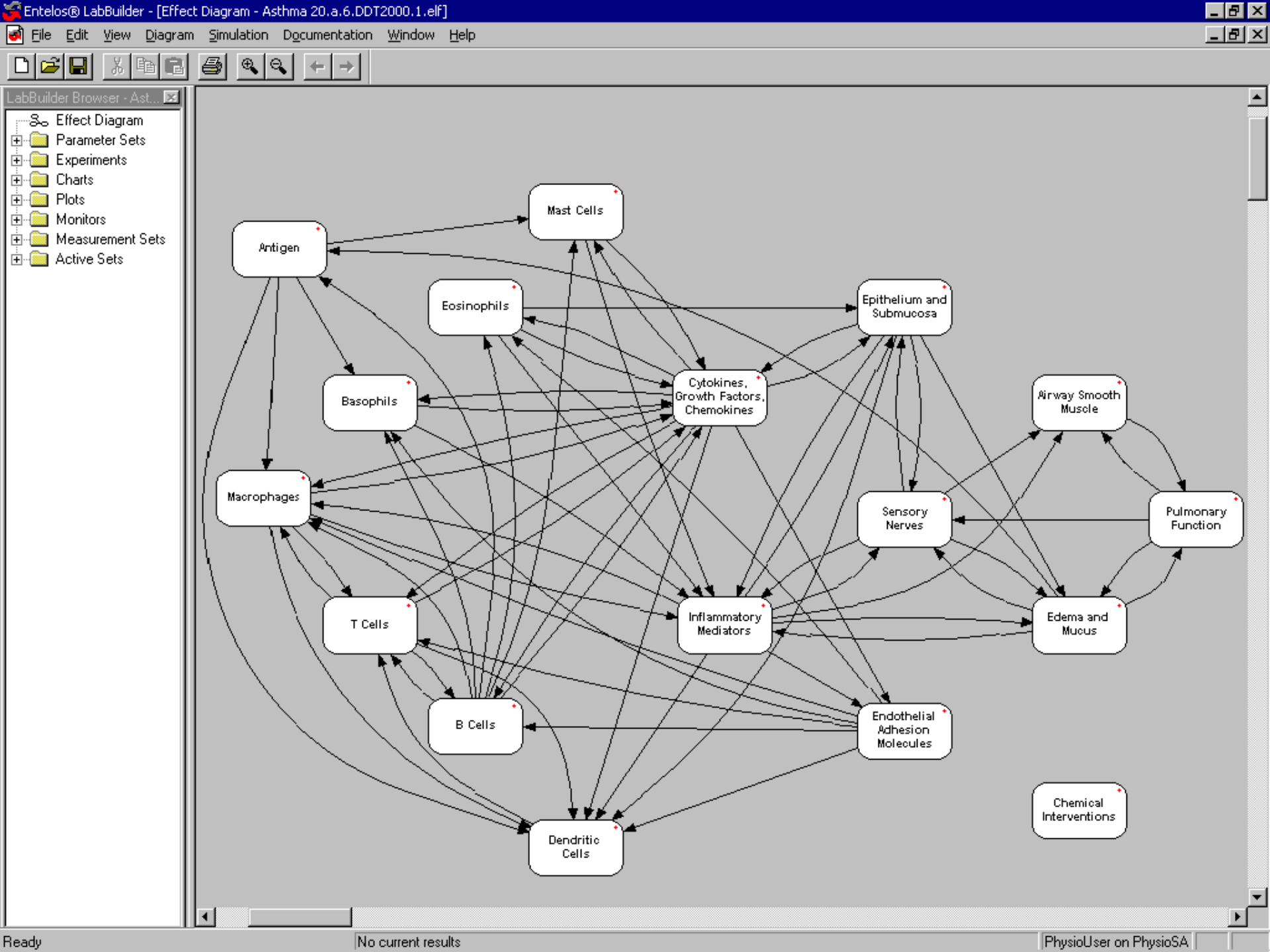
Computer Models Allow Reconstruction of Processes Across Different Scales

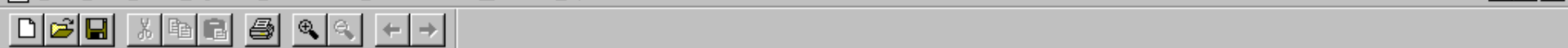


Disease Map

[illegible]

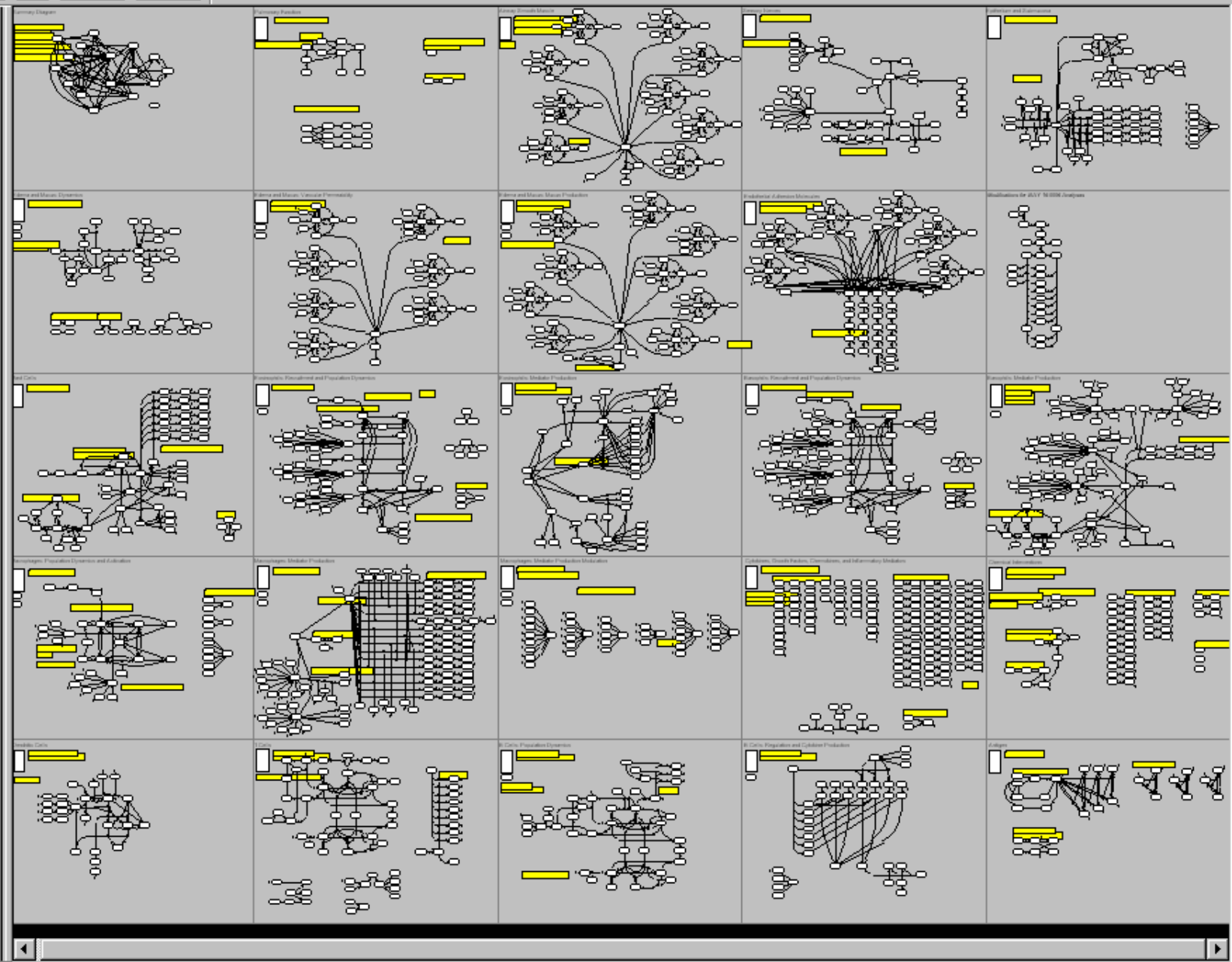
Reference Database





LabBuilder Browser - Ast...

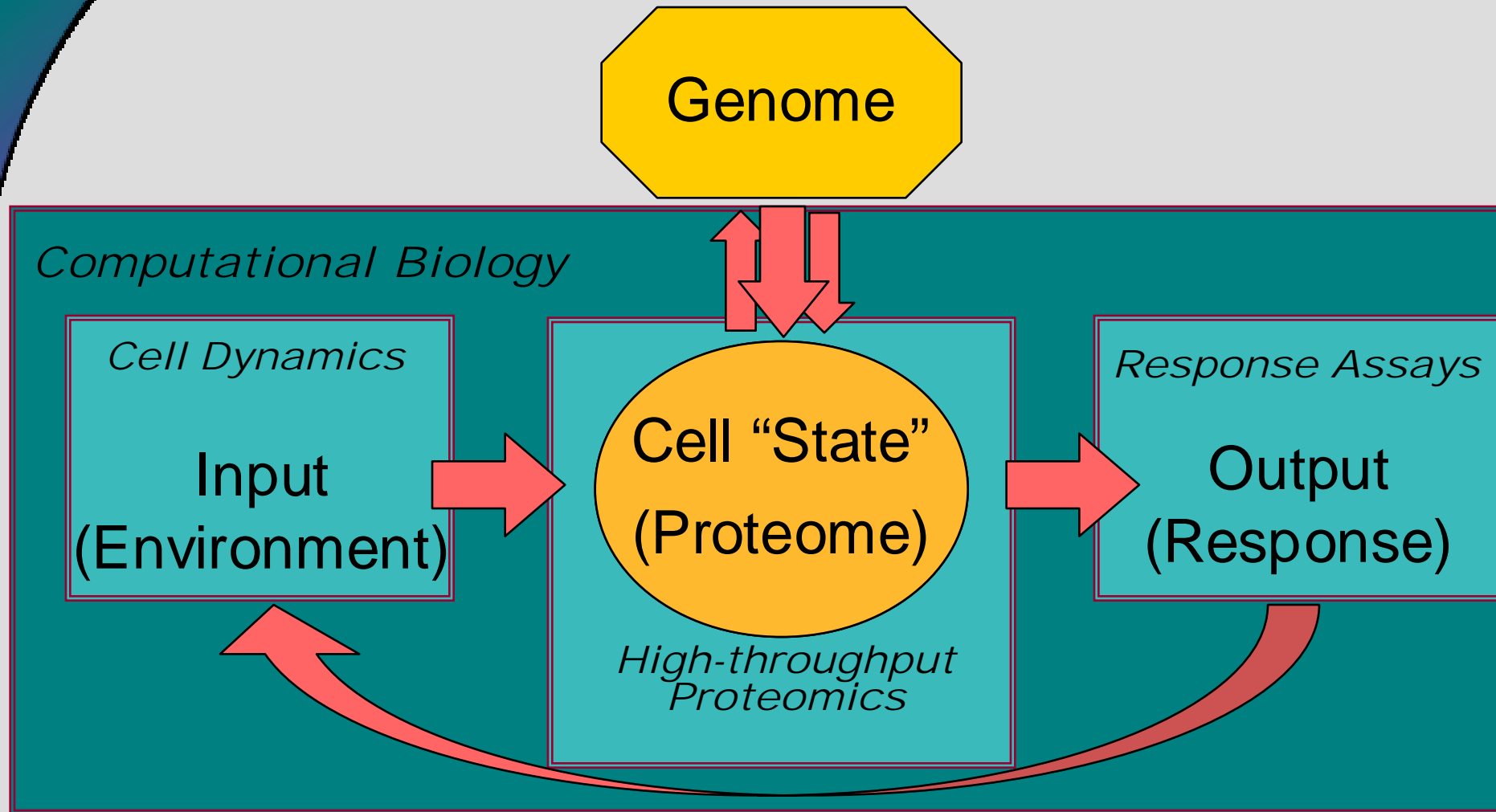
- Effect Diagram
- Parameter Sets
- Experiments
- Charts
- Plots
- Monitors
- Measurement Sets
- Active Sets



Variable Nature of Cells Confounds Structured Models of Systems

- ▶ The lowest functional level of physiological models is the cell
- ▶ It is relatively easy to specify a static input-output relationship of cells
- ▶ How do we account for variable input-output state?
- ▶ Dealing with recursive nature of cells is essential for creating realistic physiological models

Biological Organisms are Dynamic and Recursive

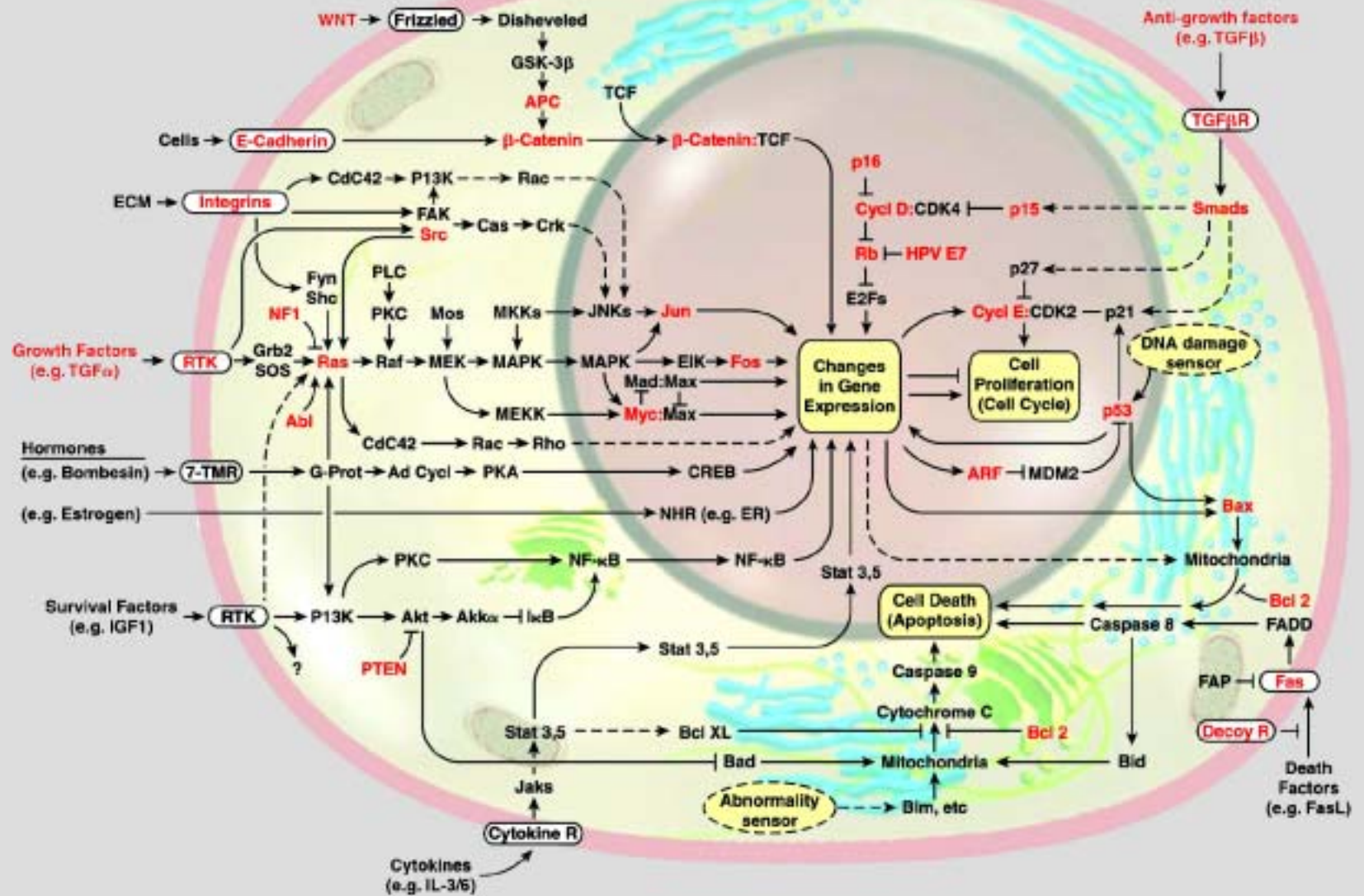


What, Where, Quantity, Quality?

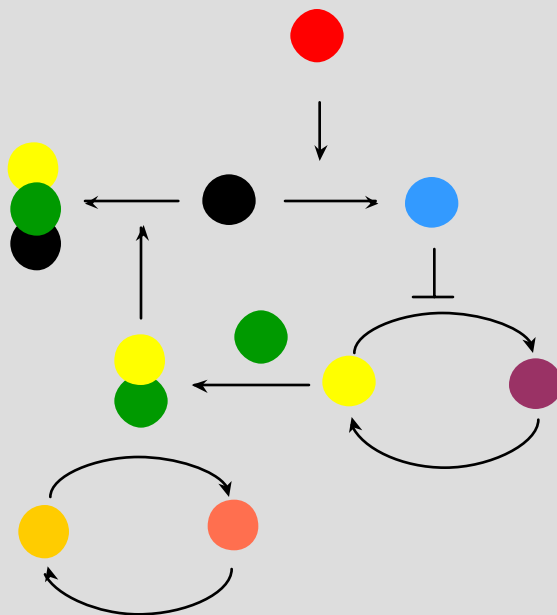
To successfully model a complex biological system, one must minimally know the following information:

- ▶ What parts are being made? (identity)
- ▶ Where are the proteins located in cell? (location)
- ▶ What are their levels? (quantity)
- ▶ How do they interact with their partners? (activity)
 - As a function of covalent modification
 - Contribution of steric restrictions
 - Forward and reverse rate constants

Cells are Regulated by a Network of Proteins



What Is Necessary to Understand a Network?



Nodes
(Components)

Connectivity
(Interactions)

**Experimental
Biology**

Spatial Organization
(Transport)

Dynamic Range
(Kinetics)

**Modeling &
Analysis**

Proteomics is Essential for Understanding Cellular Behavior

One cannot adequately model or predict cellular responses UNLESS the proteome of a given cell is first specified!

Proteomics Capabilities



Unique method for rapid generation of synthetic antibodies using high-speed flow cytometers.

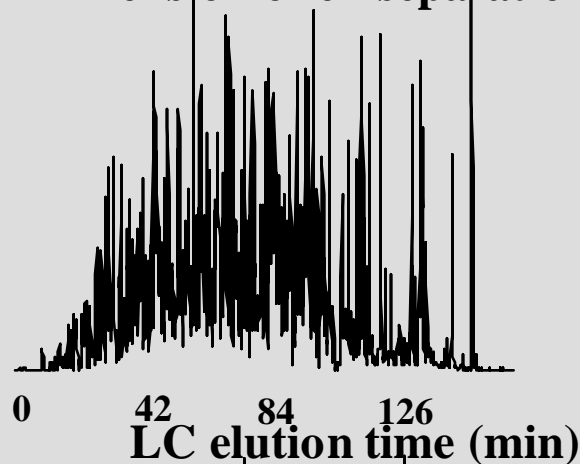
FTICR instruments provide unprecedented detail on the proteins expressed by cells under specific environmental conditions.



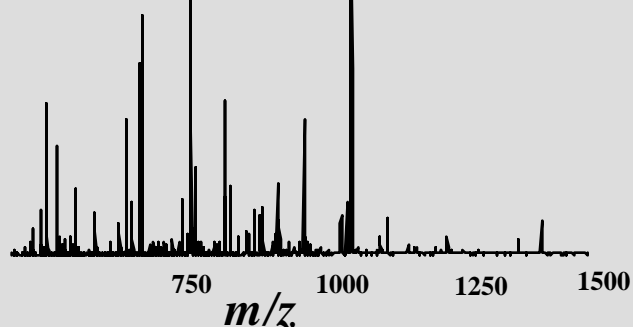
Global simultaneous quantitative proteome measurements

Proteins identified and quantified using
accurate mass and time (AMT) tags

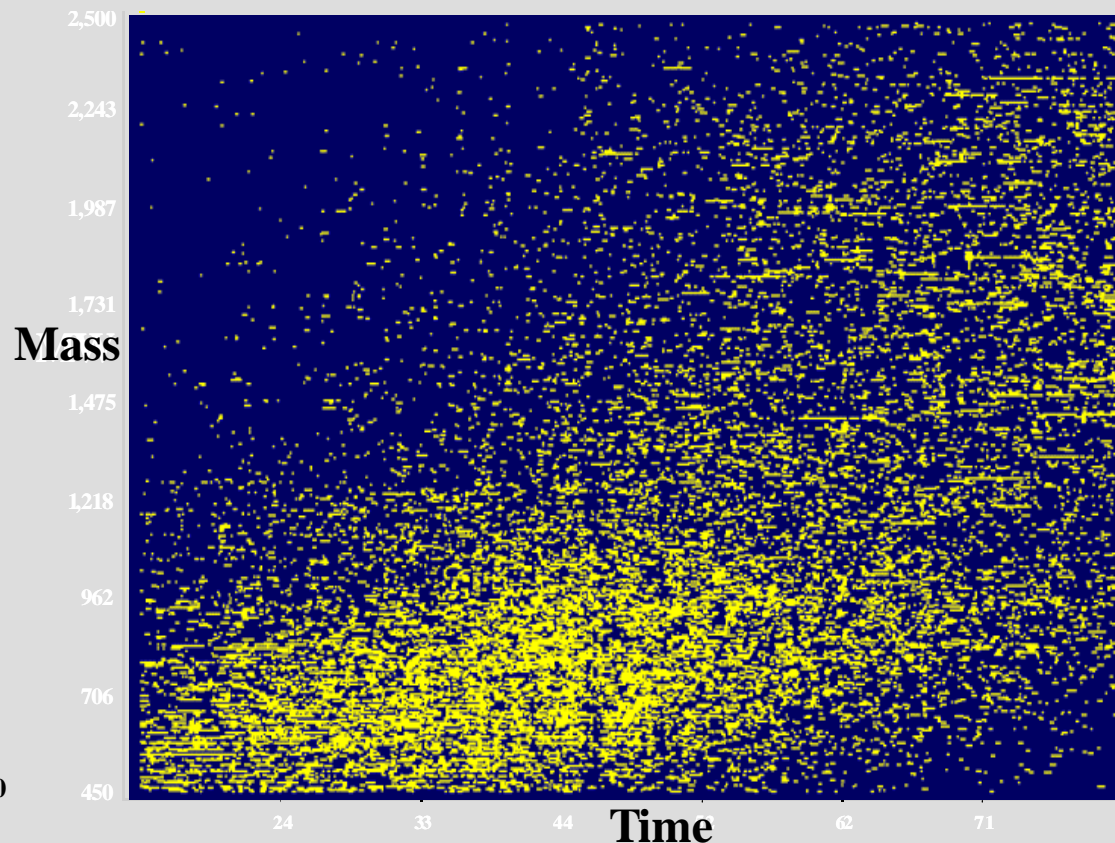
Dimension one - separation time



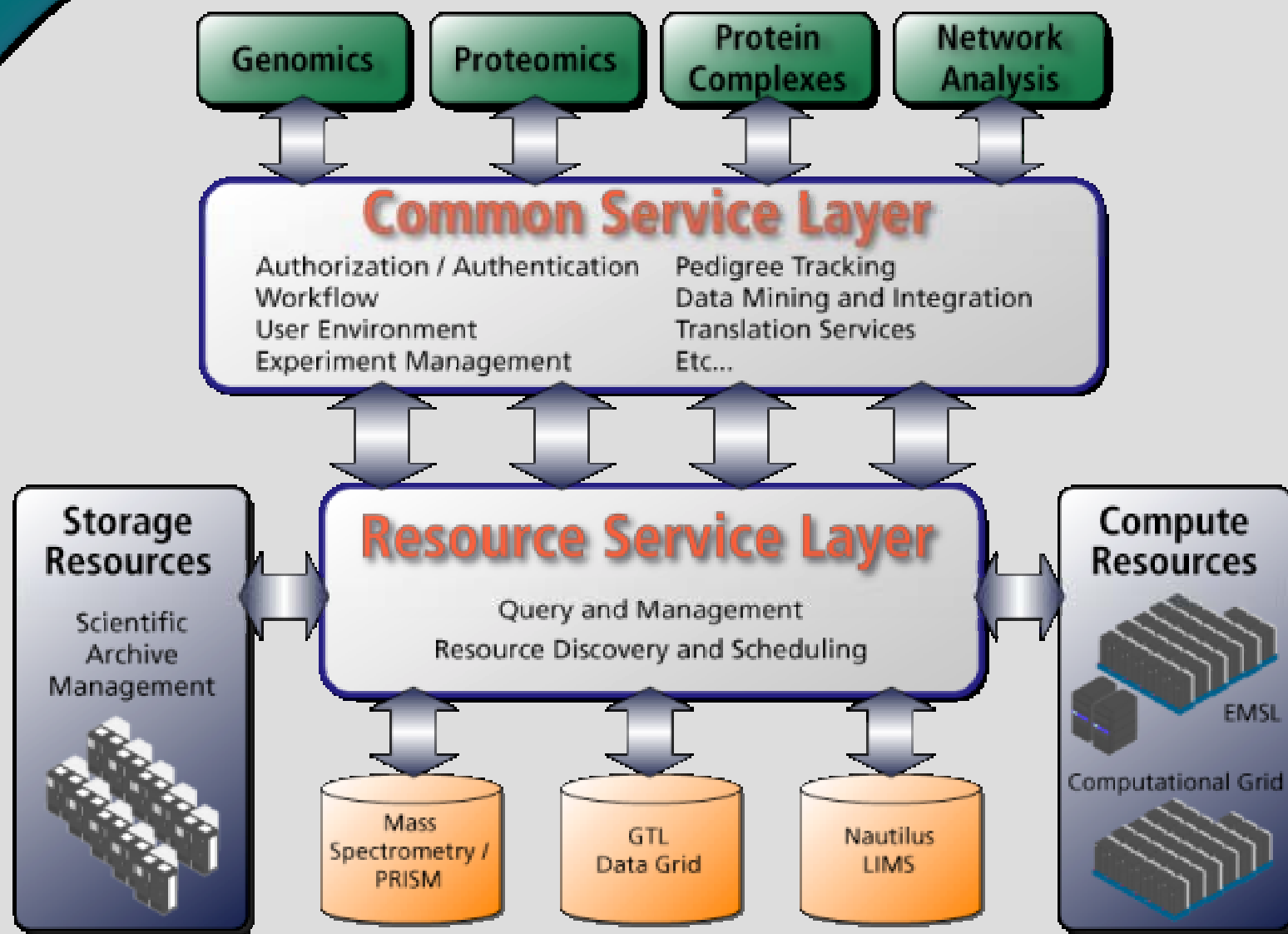
Dimension two - accurate mass



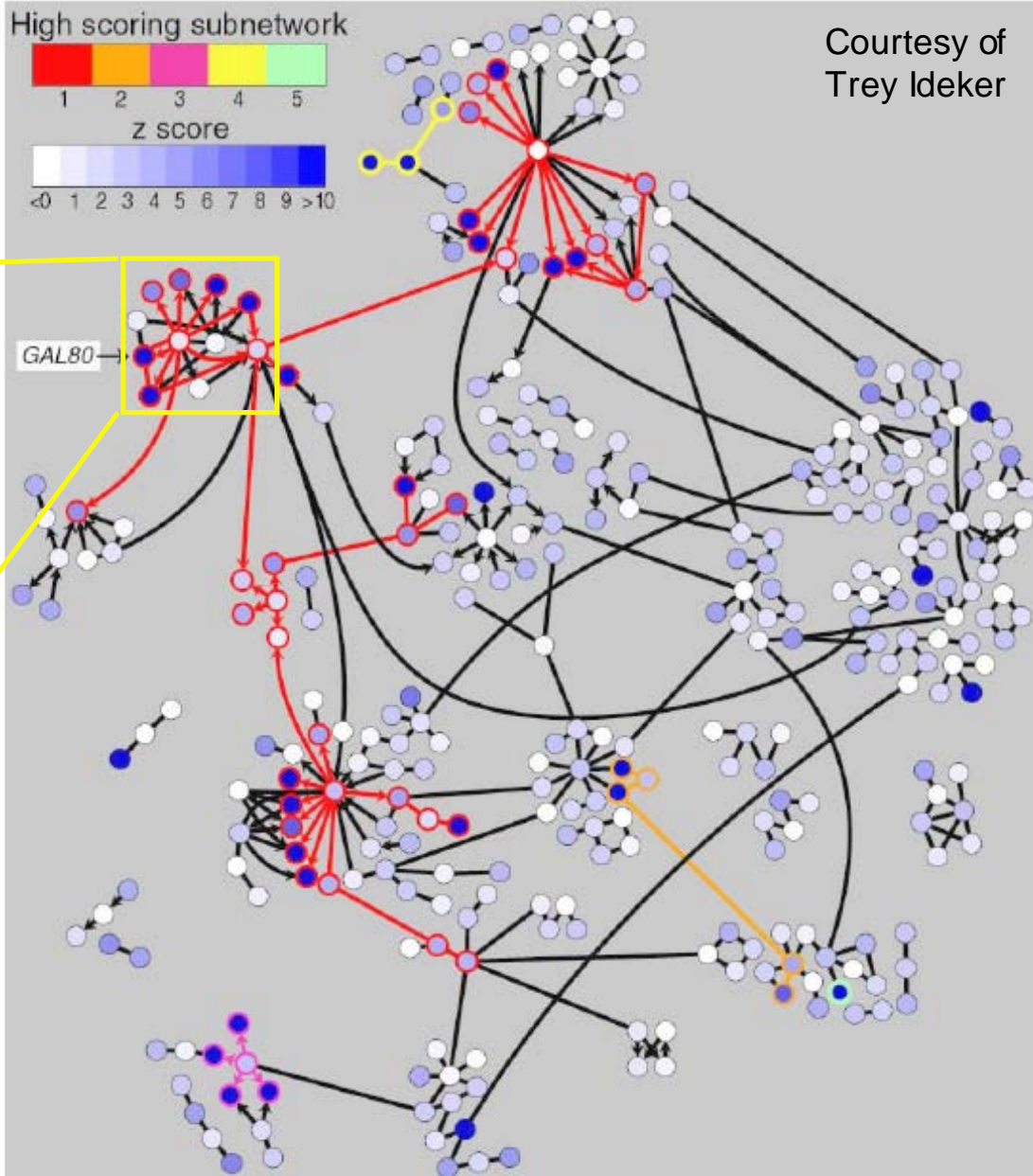
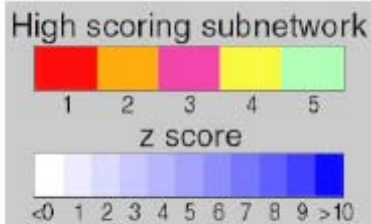
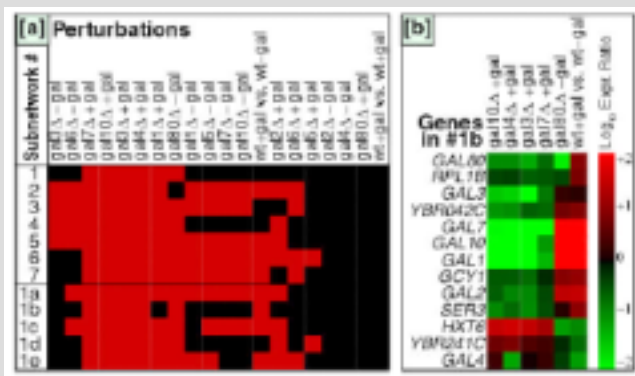
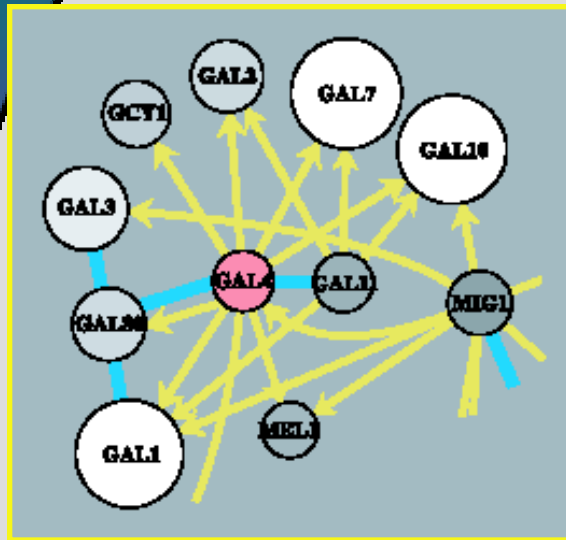
2-D display of detected peptides



Problem Solving Environment



Evaluating interaction networks with gene expression data



Courtesy of
Trey Ideker

Can biological phenomena be understood by humans?

Despite the increasingly successful collaboration between physics and biology, there are contexts in which their styles and philosophies can diverge. Nowhere more so than in 'understanding'.

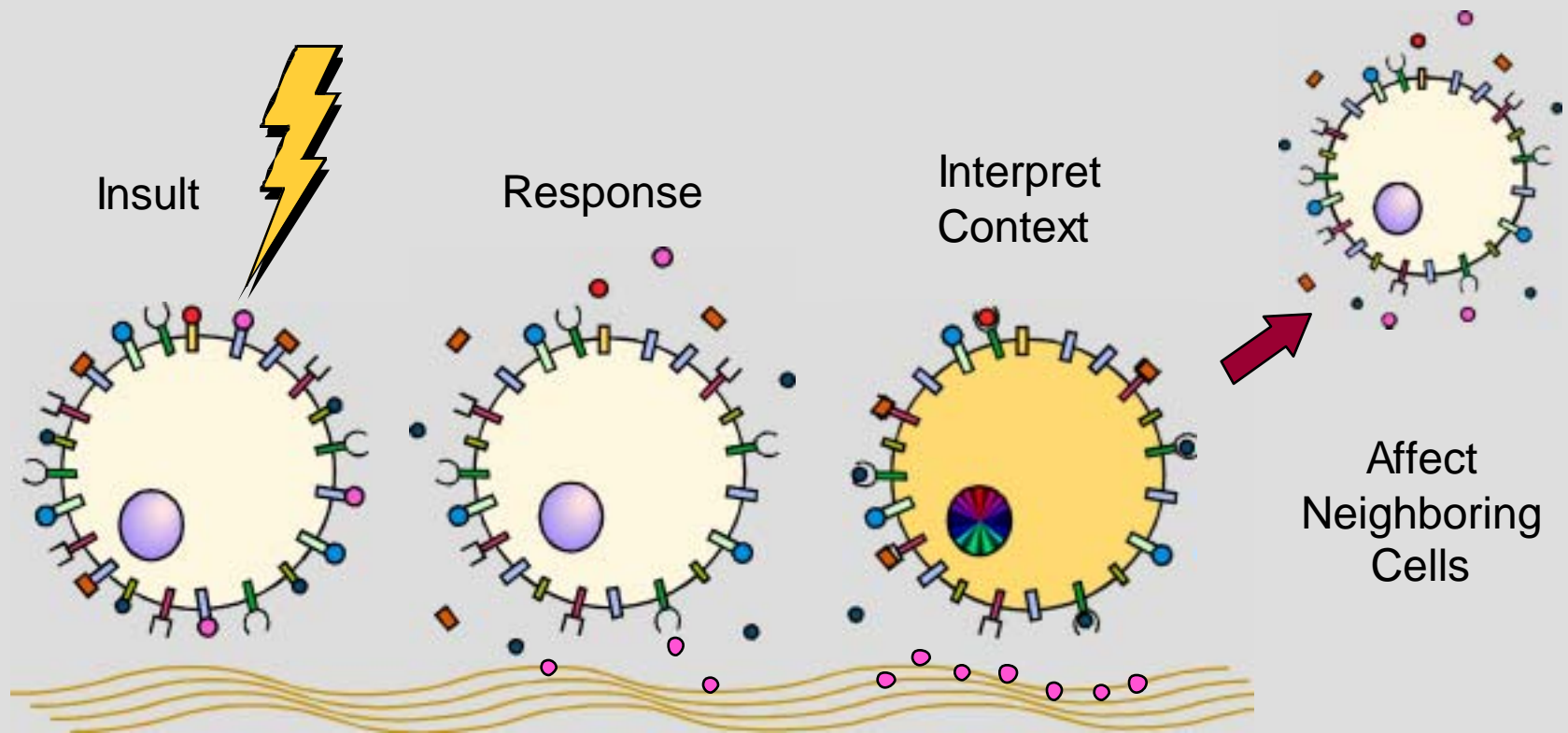
“It is nice to know that the computer understands the problem. But I would like to understand it, too.” So said the theoretical physicist Eugene Wigner when shown the results of a large quantum mechanics calculation. Now, if a theoretical physicist of a younger generation is to be believed, today's biologists are in danger of delegating to their computers the job of understanding biology. Physics Nobel laureate Robert Laughlin — who was able to understand the fractional quantum Hall effect without the aid of computers — was invited to a conference in San Diego earlier this month on quantitative challenges in the post-genome-sequence era. His job was to stir things up, and he duly did so. His remarks sparked a spirited defence of the post-genome-sequence biological agenda, but also prompted some

Laughlin worries that in the post-genome era, biologists will be too busy accumulating facts and modelling them to seek simplification and underlying principles. The fact-gathering tendency is apparent not just in structural genomics, but also in functional genomics (where the aim is to identify the role of each gene in the genome) and proteomics (with a similar aim for each protein in the cell or organism). Evidently, there are enough facts to keep biologists busy gathering them for decades, so when will they have time to think?

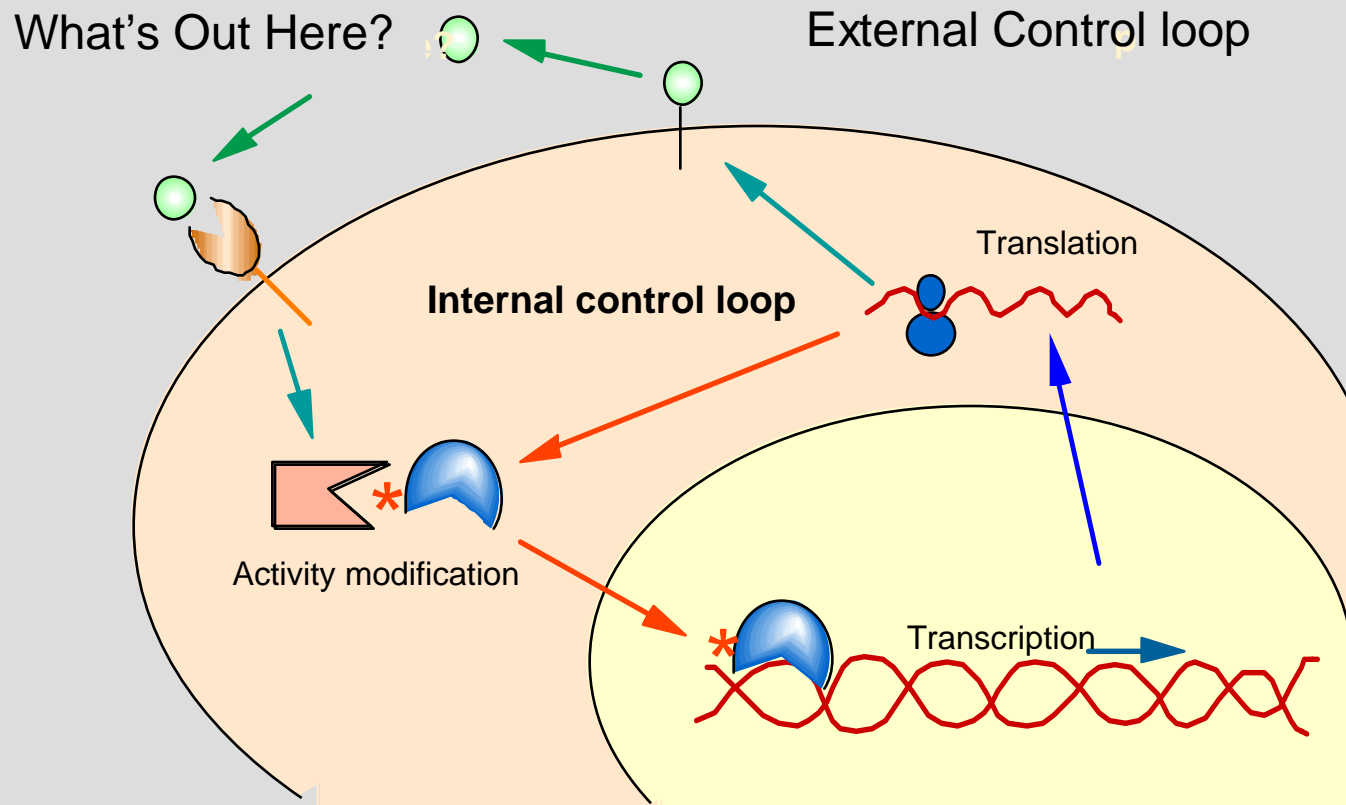
In defence of modelling

One answer, conveyed forcefully at the conference by Klaus Schulten (for protein-structure studies) and David Botstein (for

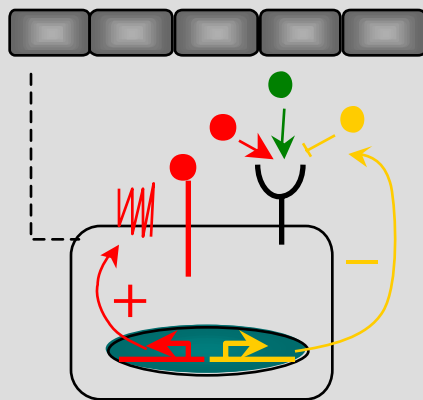
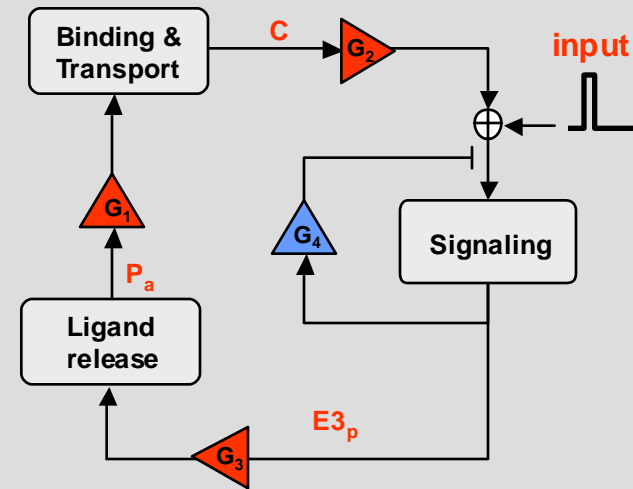
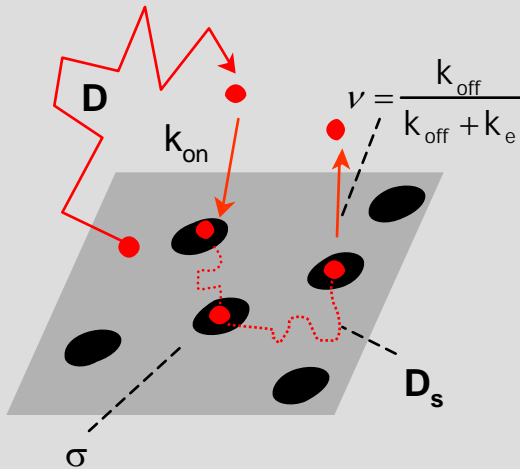
Model of How Cells Respond to a General Stressor



Autocrine Loops are Externalized Control Systems



Our Tools: Modeling and Analysis



Models:

deterministic and stochastic

Analysis:

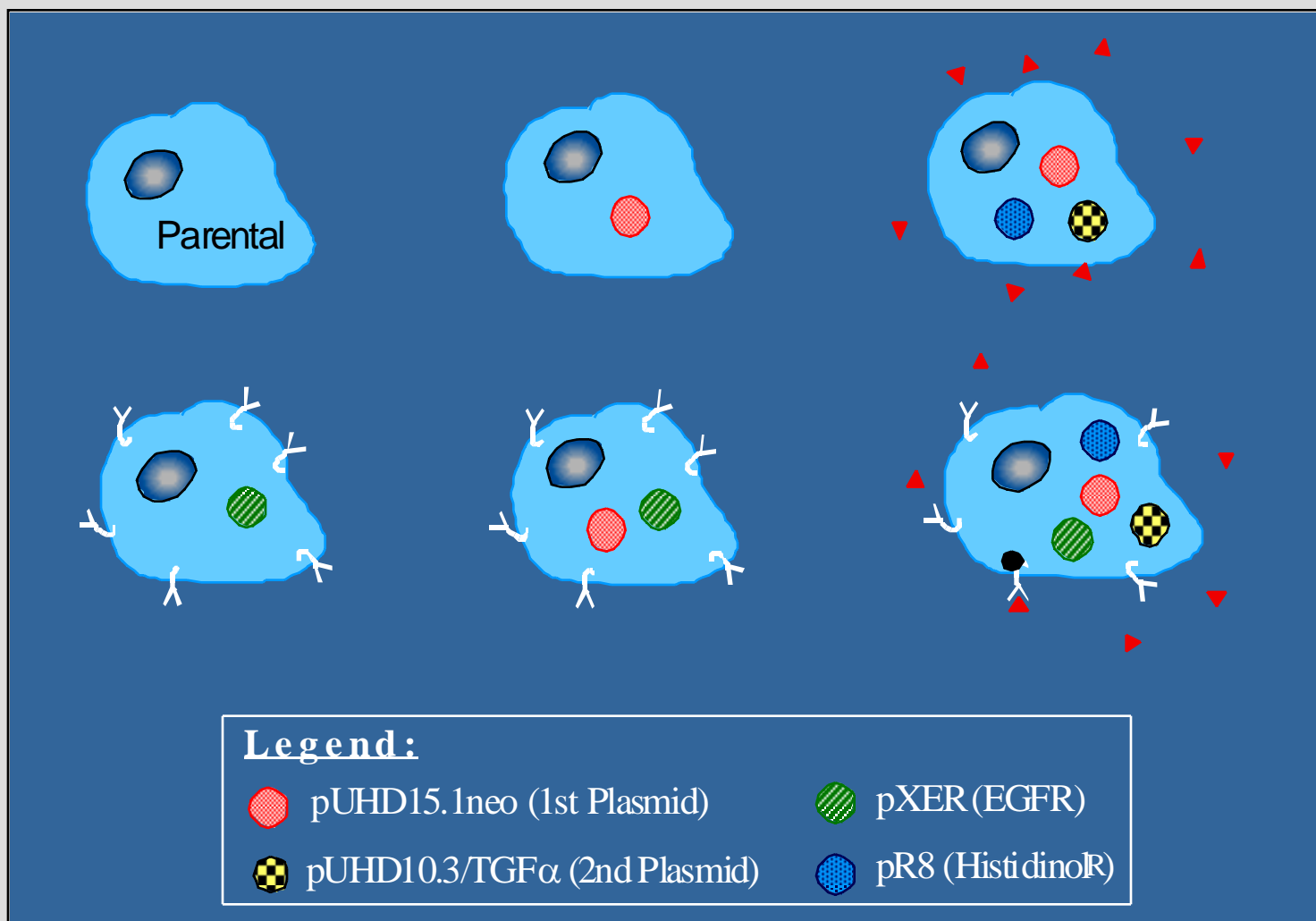
lumped and distributed

theory and computation

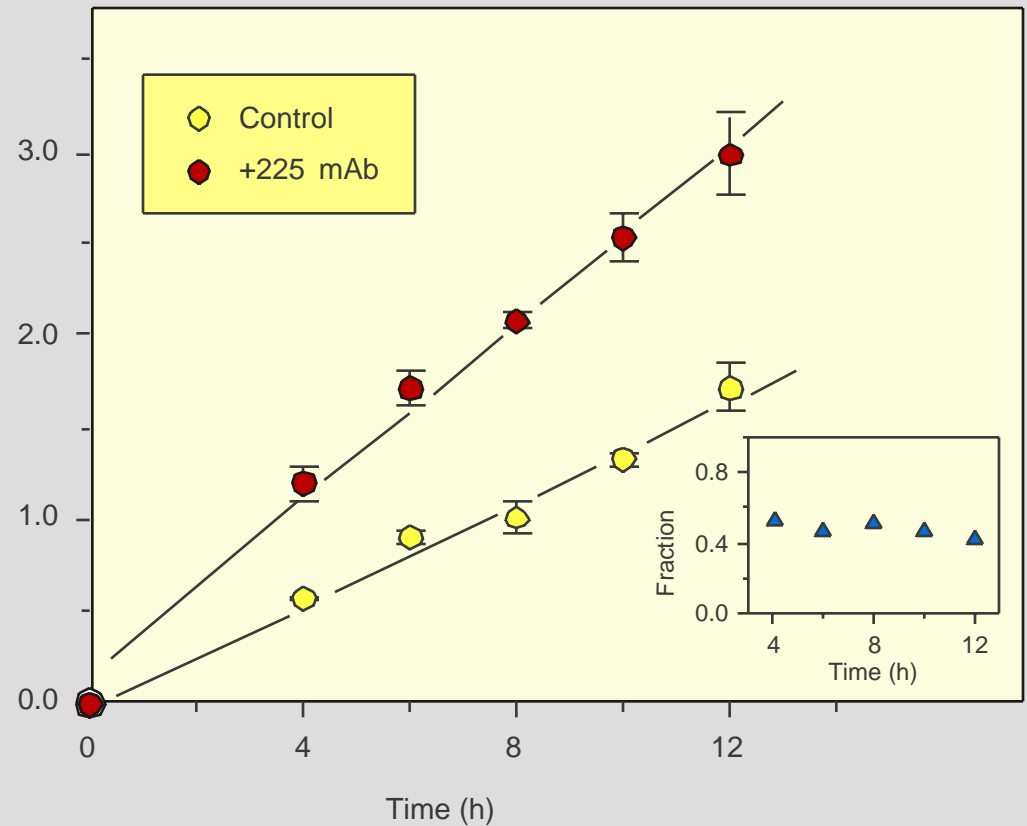
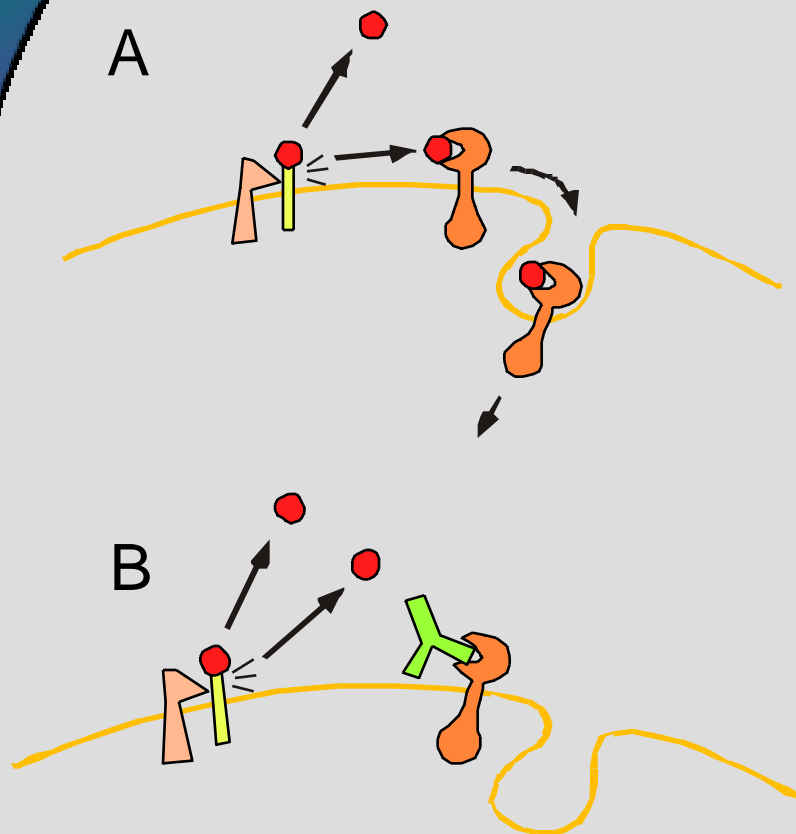
Applications:

experimental systems

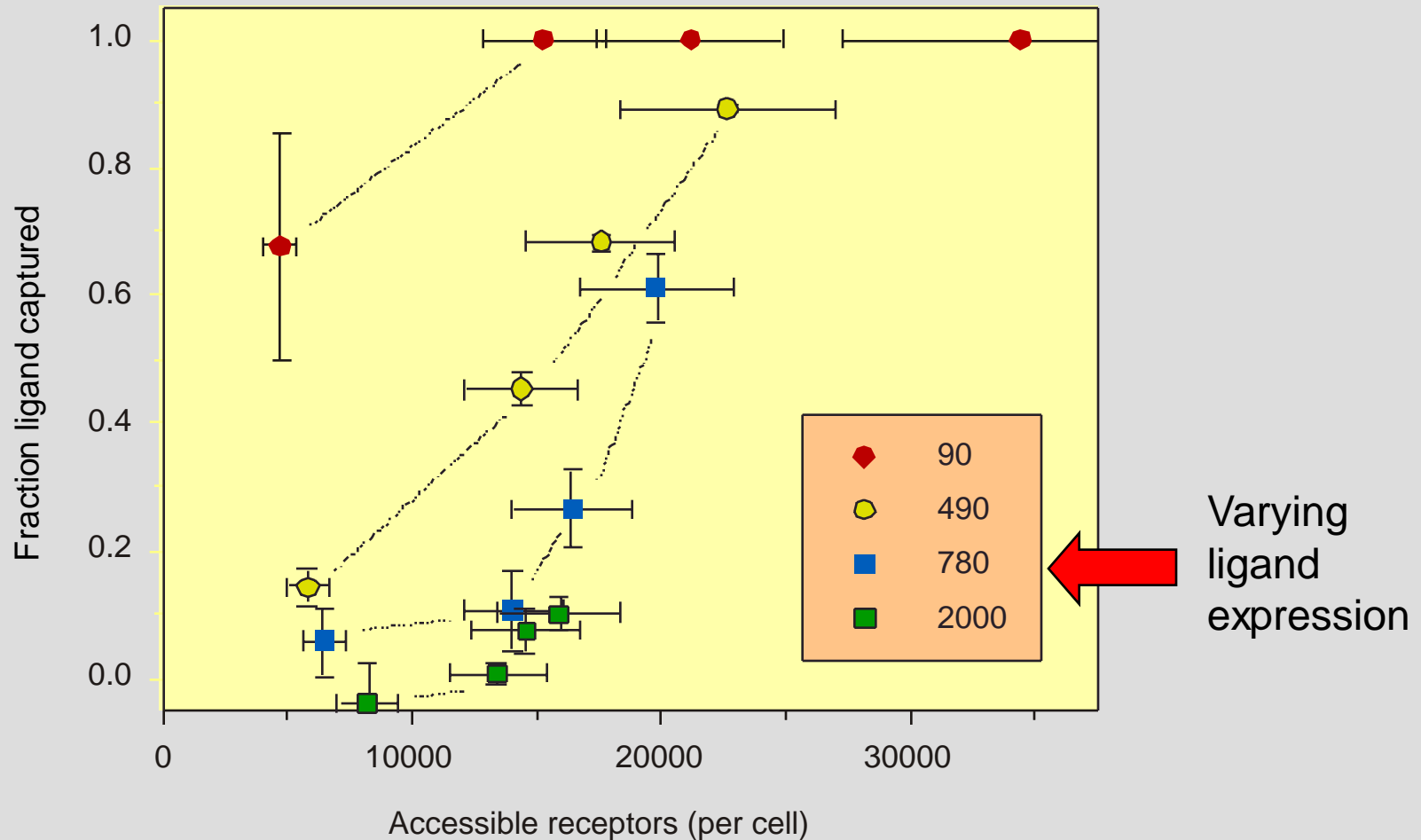
Reconstituting an Autocrine Cell



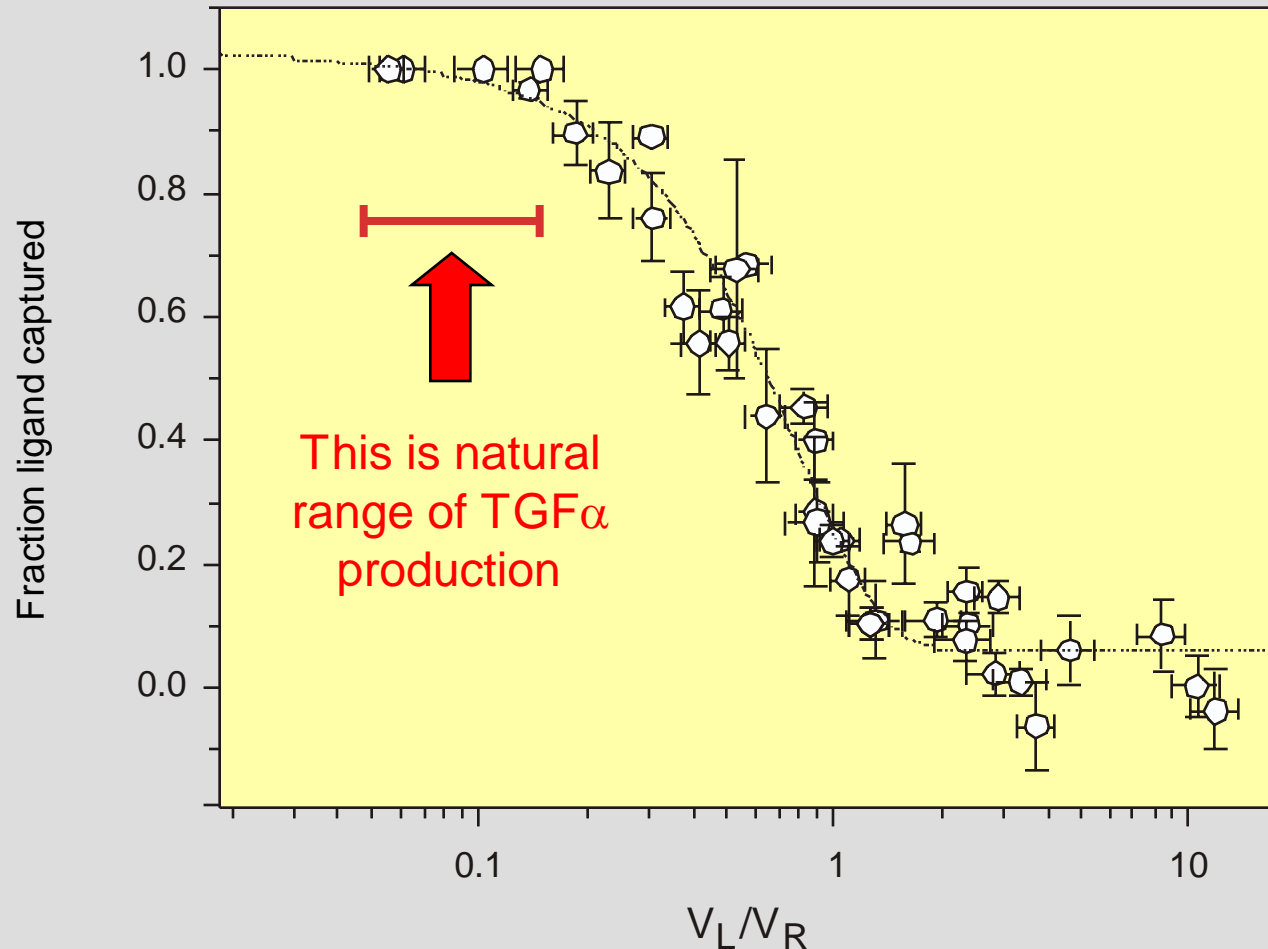
Fractional Capture of EGF



Autocrine Ligand Capture



Simple Rule of Autocrine Capture



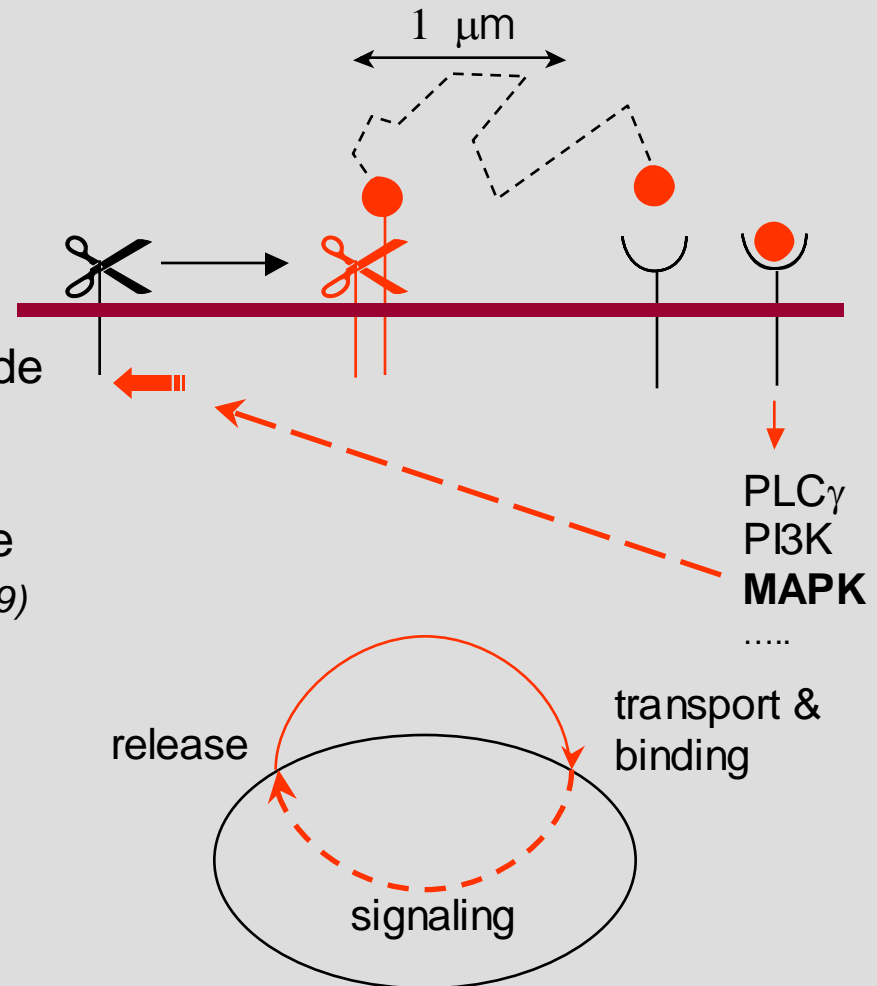
Ligand Comes Back to the Same Cell...

So What?

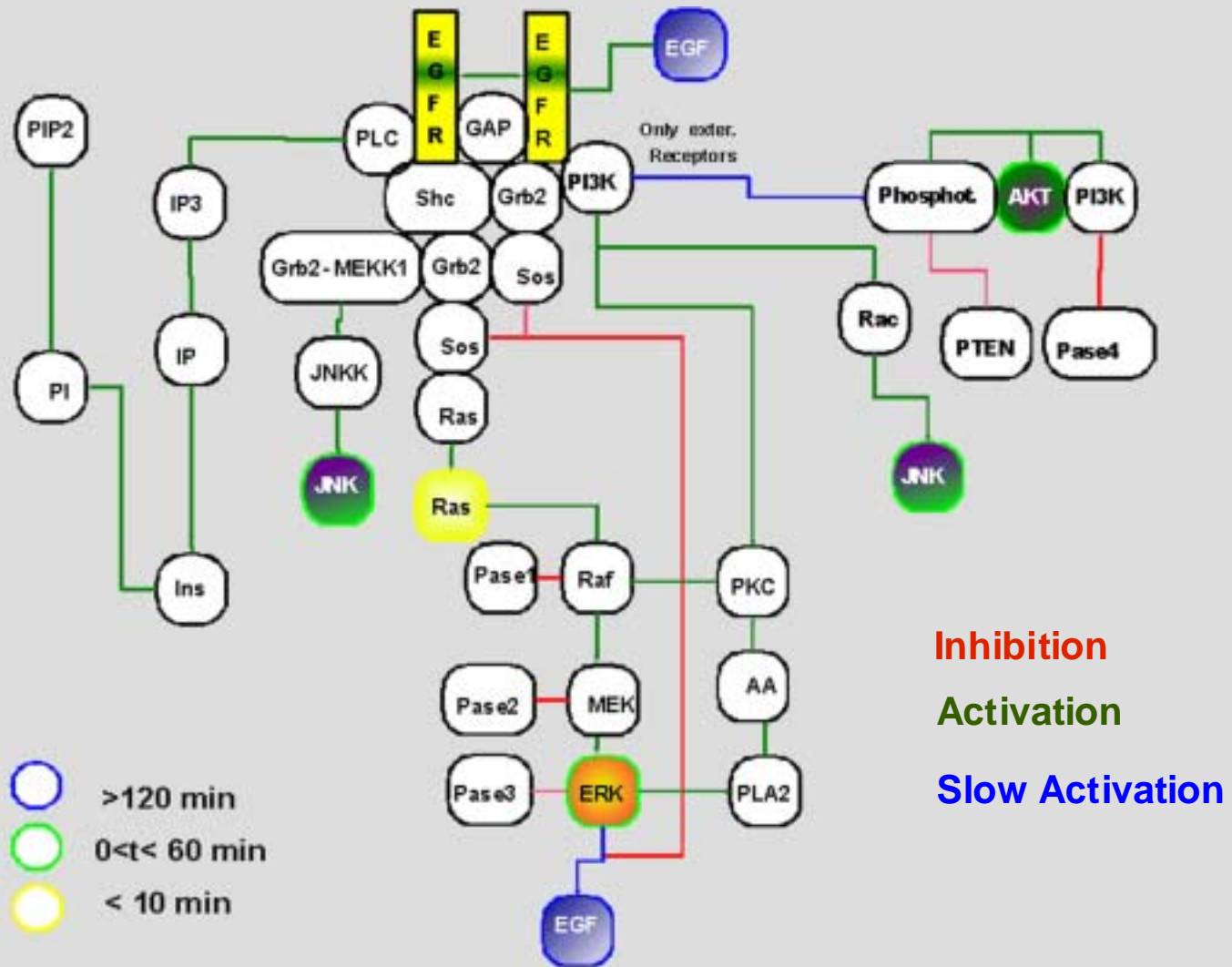
- 1) Autocrine ligands come back
(*transport models*)
- 2) Bound receptor stimulates MAPK cascade
(*common knowledge*)
- 3) MAPK cascade stimulates ligand release
(*Fan & Derynck, 1999; Gechtman et.al, 1999*)



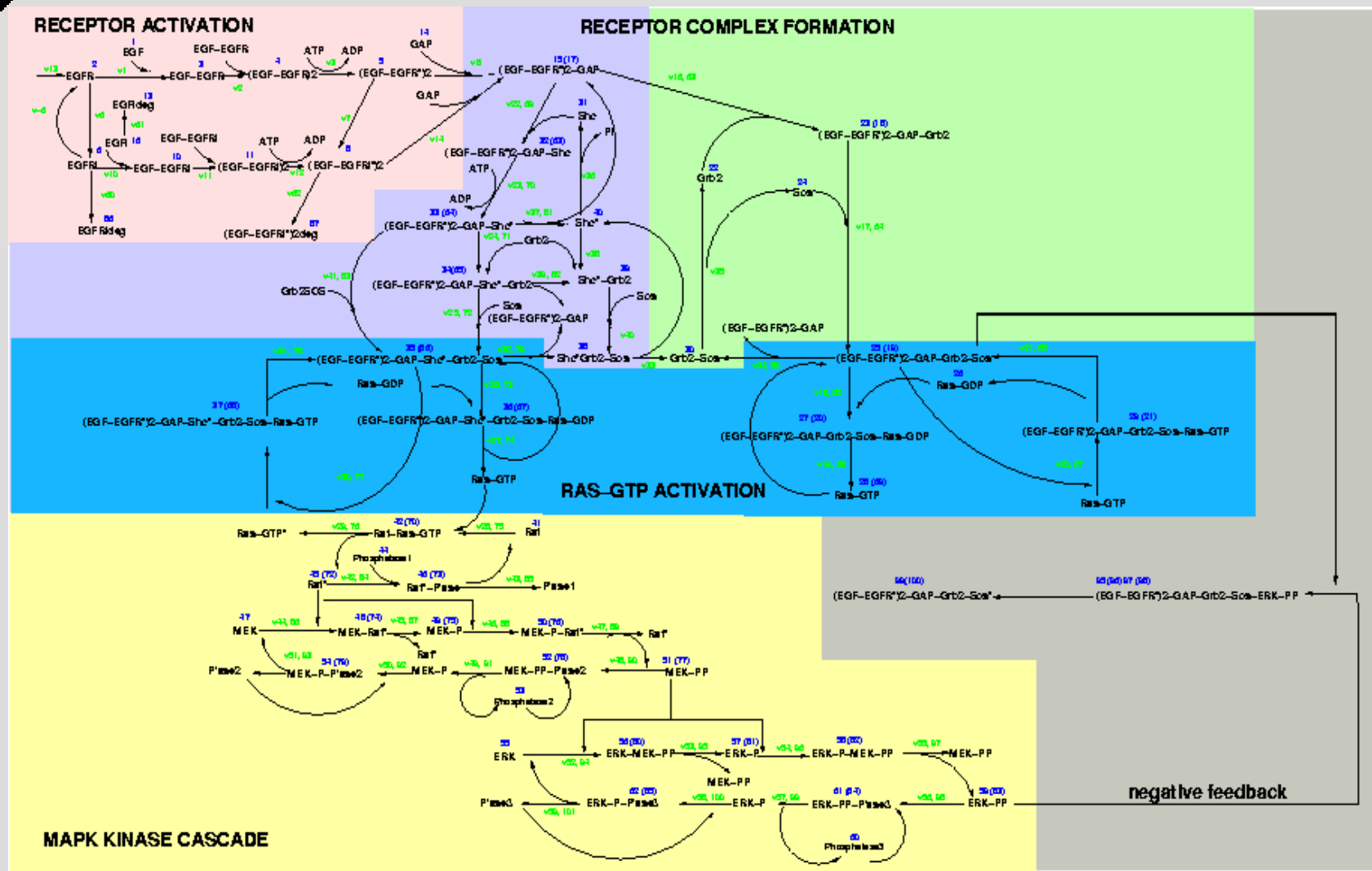
Ligand release is autocatalytic



EGFR Core Signaling Network

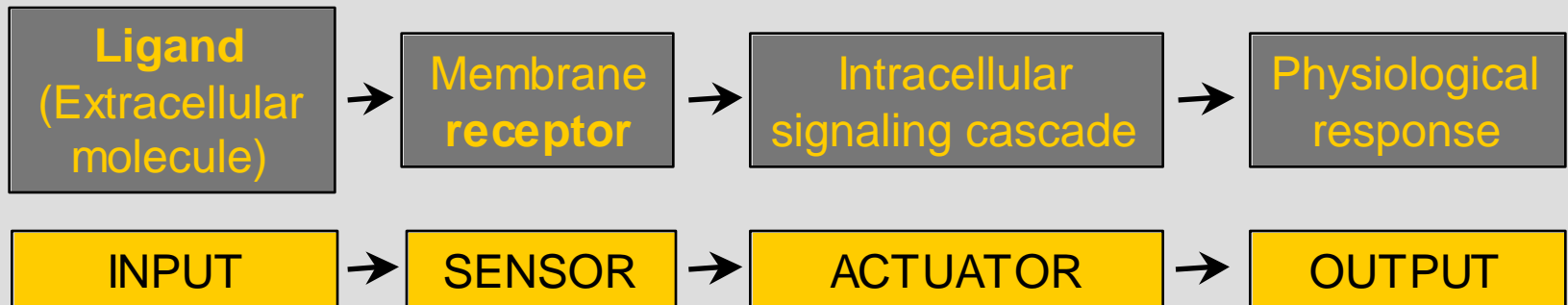
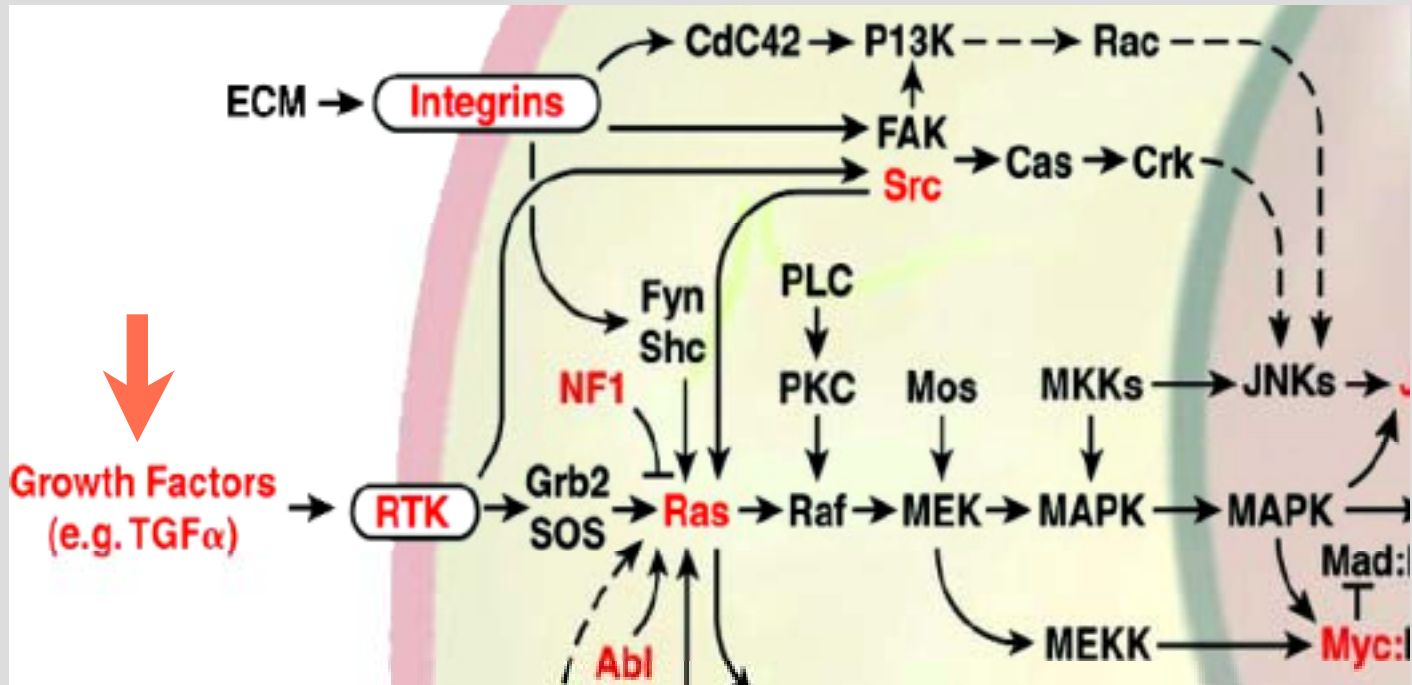


Biochemical Reaction Scheme



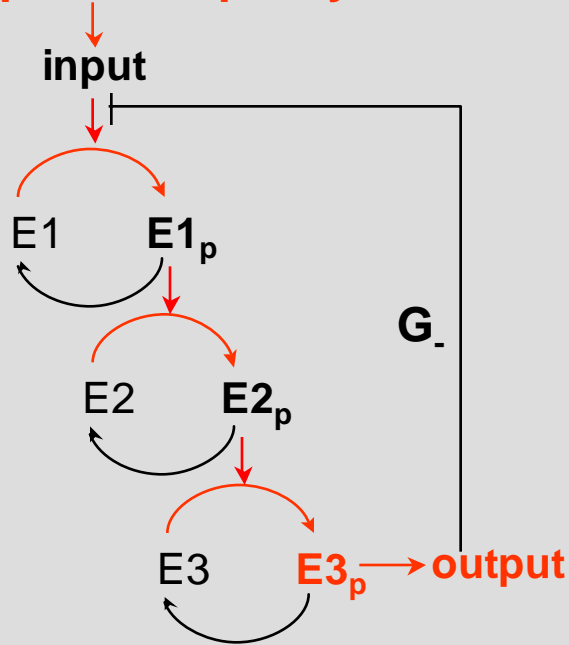
Schoeberl et al., *Nature Biotech.* [2002]

Signaling Through Growth Factor Receptors



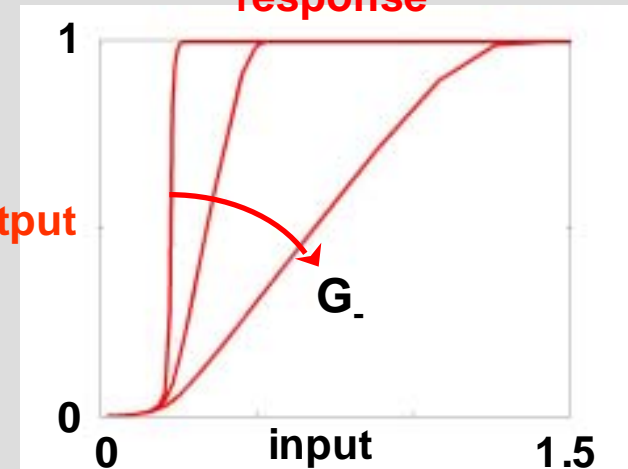
High-level Model of MAPK Cascade

receptor occupancy



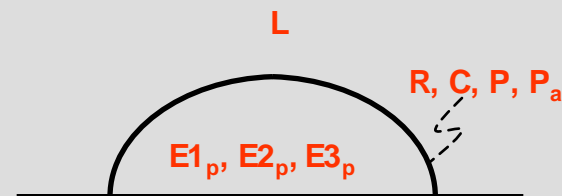
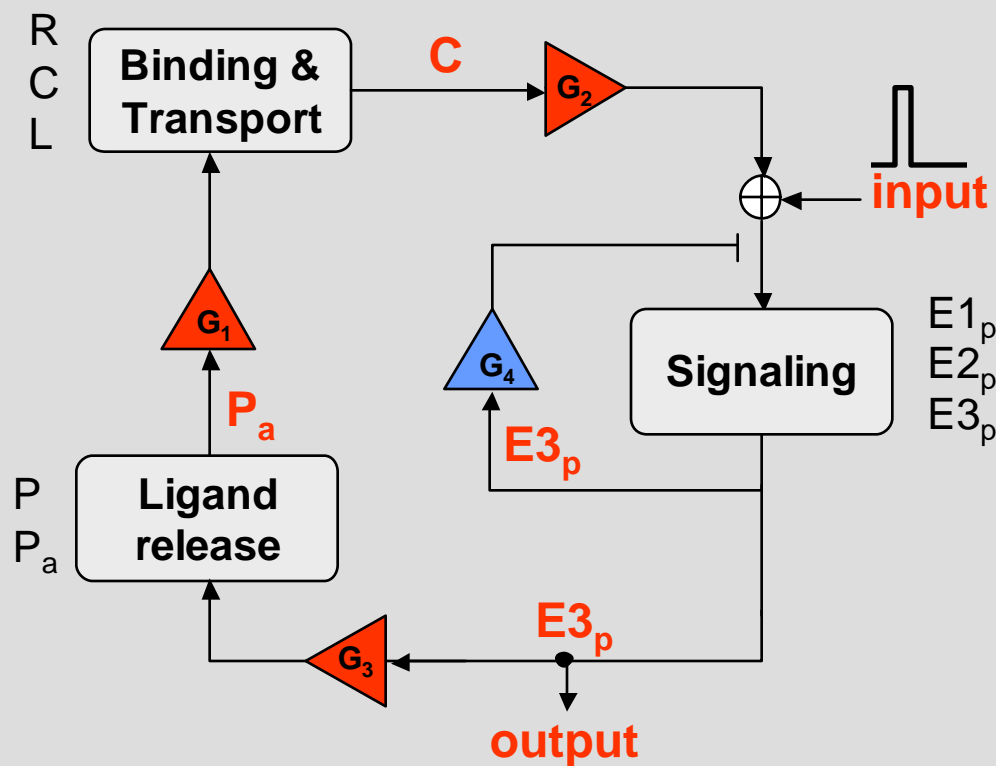
$$\frac{E_{3p}}{E_{3p} + E_3} \text{ Output}$$

ultrasensitive response



- three stages
- each stage operates near saturation
- Michaelis-Menten kinetics

Model Autocrine Cell:



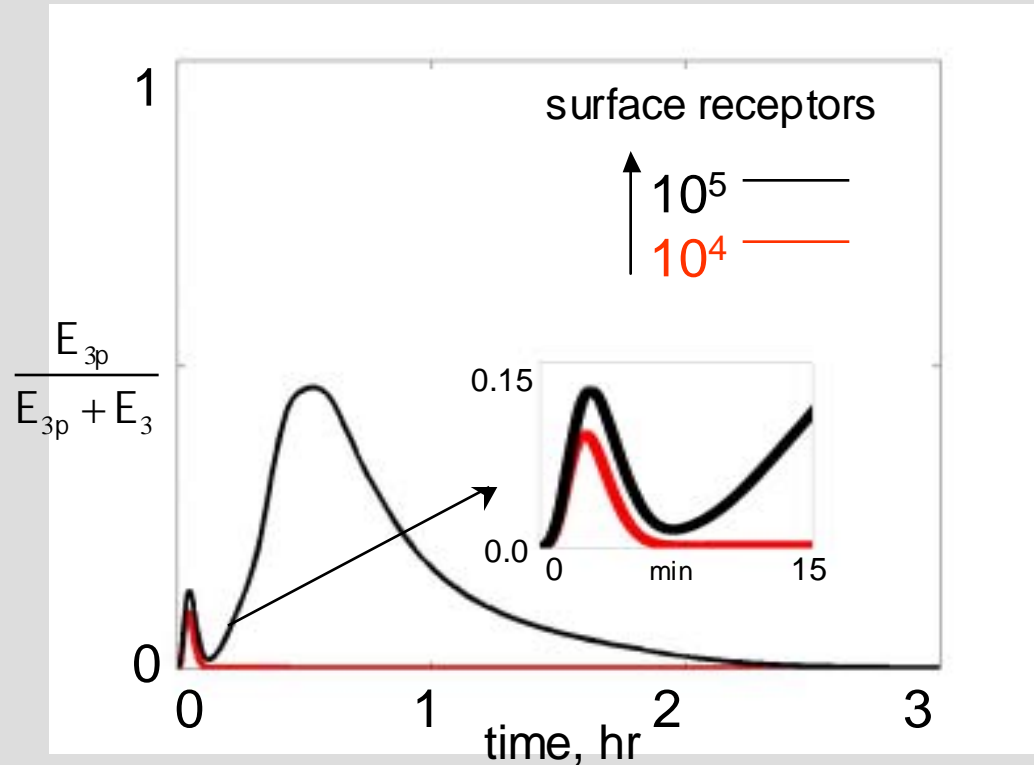
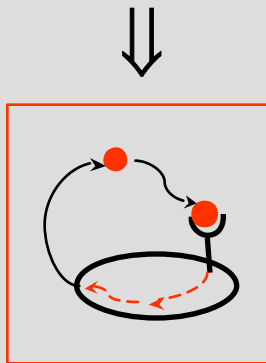
$$\begin{aligned} \frac{1}{k_{off}} \frac{d\bar{R}}{dt} &= -\bar{R} \frac{G_1 \bar{P}_a + Da \bar{C}}{1 + Da \bar{R}} + \gamma(1 - \bar{R}) + \bar{C} \\ \frac{1}{k_{off}} \frac{d\bar{C}}{dt} &= \bar{R} \frac{G_1 \bar{P}_a + Da \bar{C}}{1 + Da \bar{R}} - \frac{\bar{C}}{1 - \delta} \\ \frac{de_{1p}}{dt} &= \frac{I_0 + G_2 R_T \bar{C}}{1 + G_4 e_{3p}} \frac{1 - e_{1p}}{K_{m,1} + (1 - e_{1p})} - \frac{V_{max,3} e_{1p}}{K_{m,3} + e_{1p}} \\ \frac{de_{2p}}{dt} &= \frac{k_2 e_{1p} (1 - e_{2p})}{K_{m,2} + (1 - e_{2p})} - \frac{V_{max,4} e_{2p}}{K_{m,4} + e_{2p}} \\ \frac{de_{3p}}{dt} &= \frac{k_3 e_{2p} (1 - e_{3p})}{K_{m,3} + (1 - e_{3p})} - \frac{V_{max,6} e_{3p}}{K_{m,6} + e_{3p}} \\ \frac{1}{k_e^P} \frac{d\bar{P}}{dt} &= \mu(1 - \bar{P}) - (v_0 + G_3 e_{3p}) \bar{P} \\ \frac{1}{k_e^P} \frac{d\bar{P}_a}{dt} &= (v_0 + G_3 e_{3p}) \bar{P} - \bar{P}_a \end{aligned}$$

Autocrine Loops Modulate Extracellular Signals

Multiple Excitations in a Closed-Loop System



Primary excitation: *minutes*
Secondary excitation: *hours*

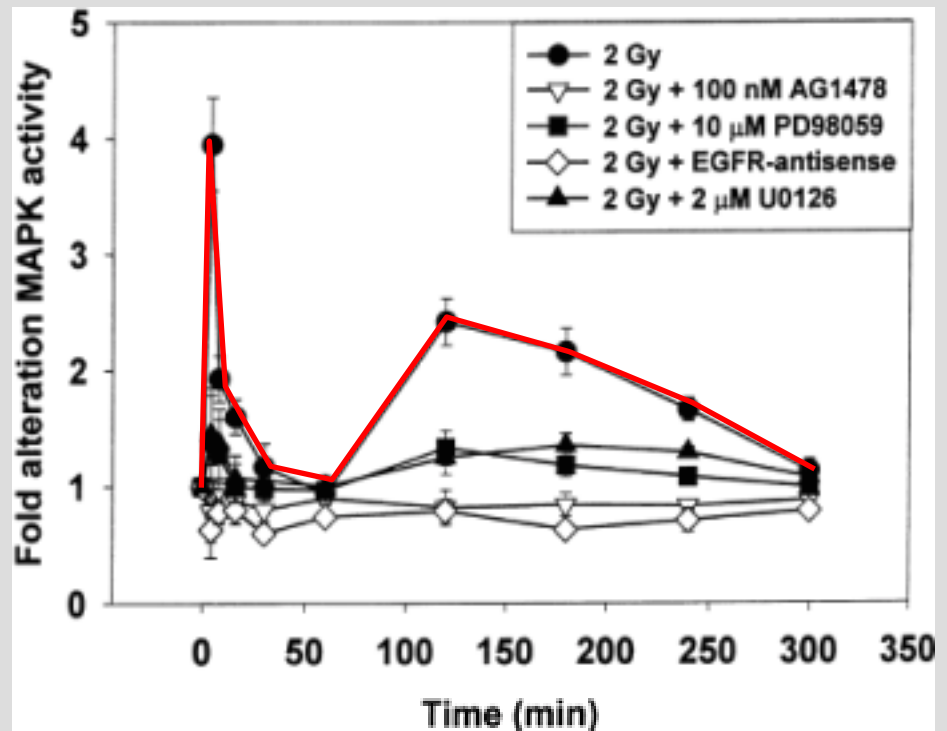
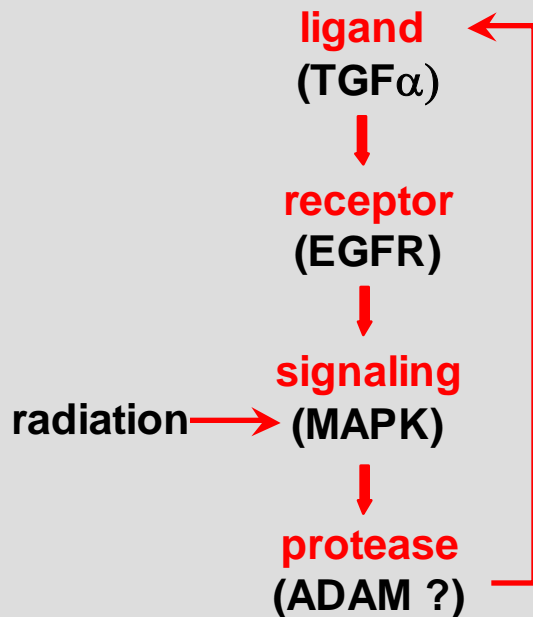


Does this really happen?

Multiple Excitations (Experiment)

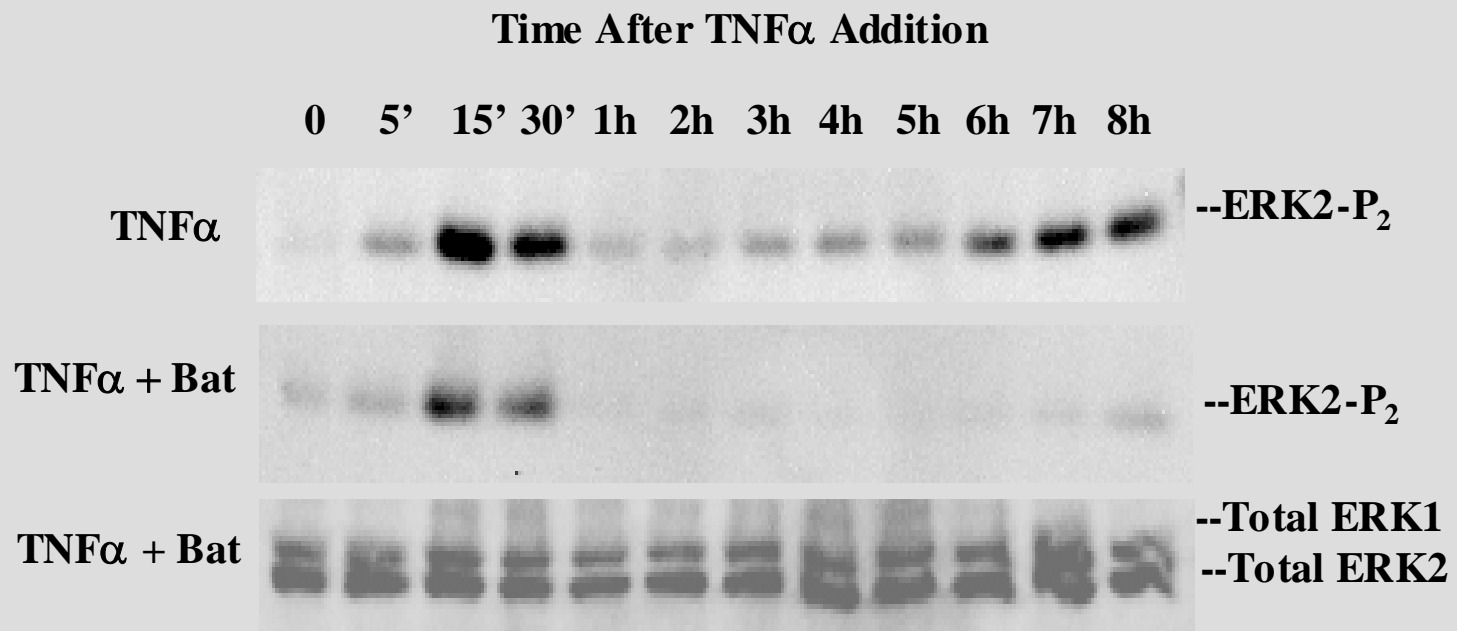
Dent et.al., *Radiation Research*, 2000

“Radiation-induced release of TGF α activates the EGFR and MAPK pathway in carcinoma cells, leading to increased proliferation and protection from radiation-induced cell death”

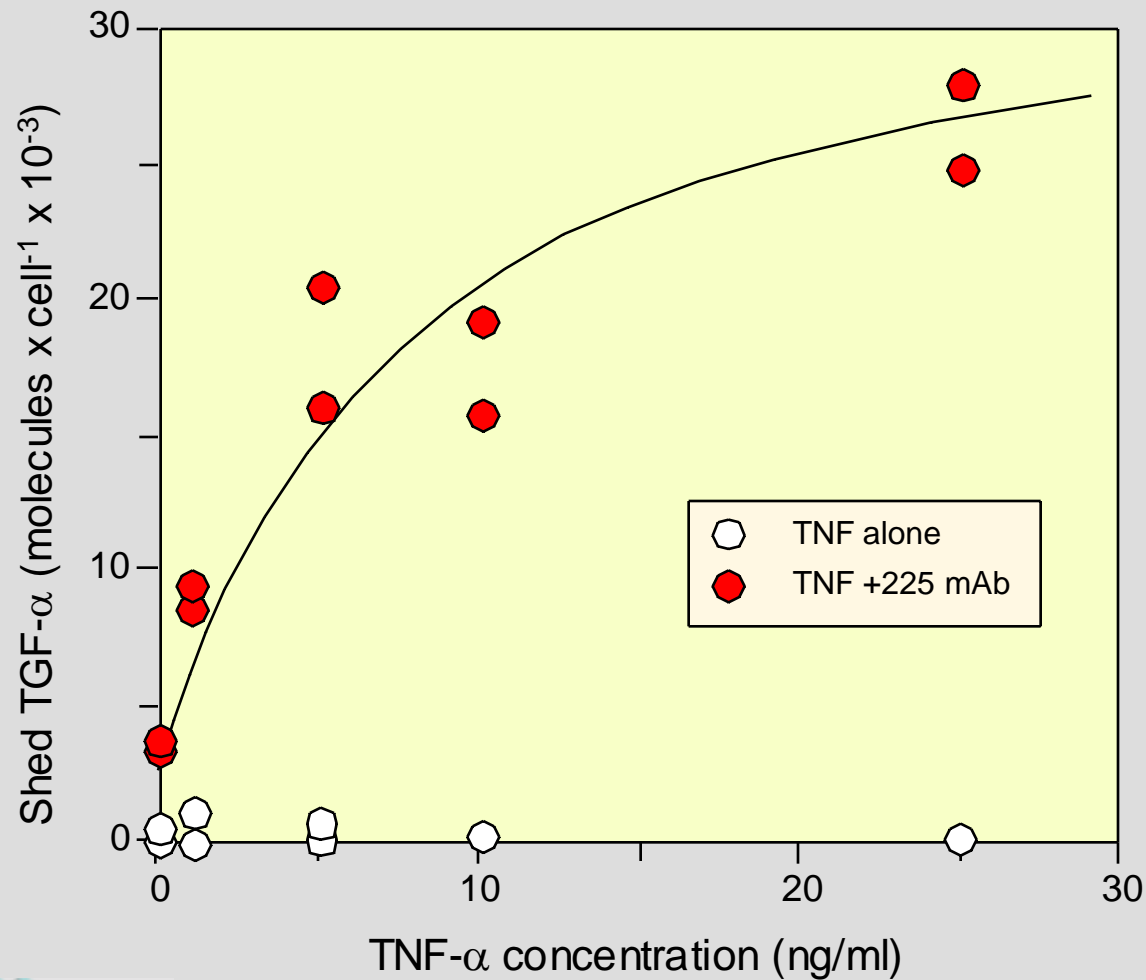


The model accounts for the secondary MAPK excitations in response to pulses of radiation

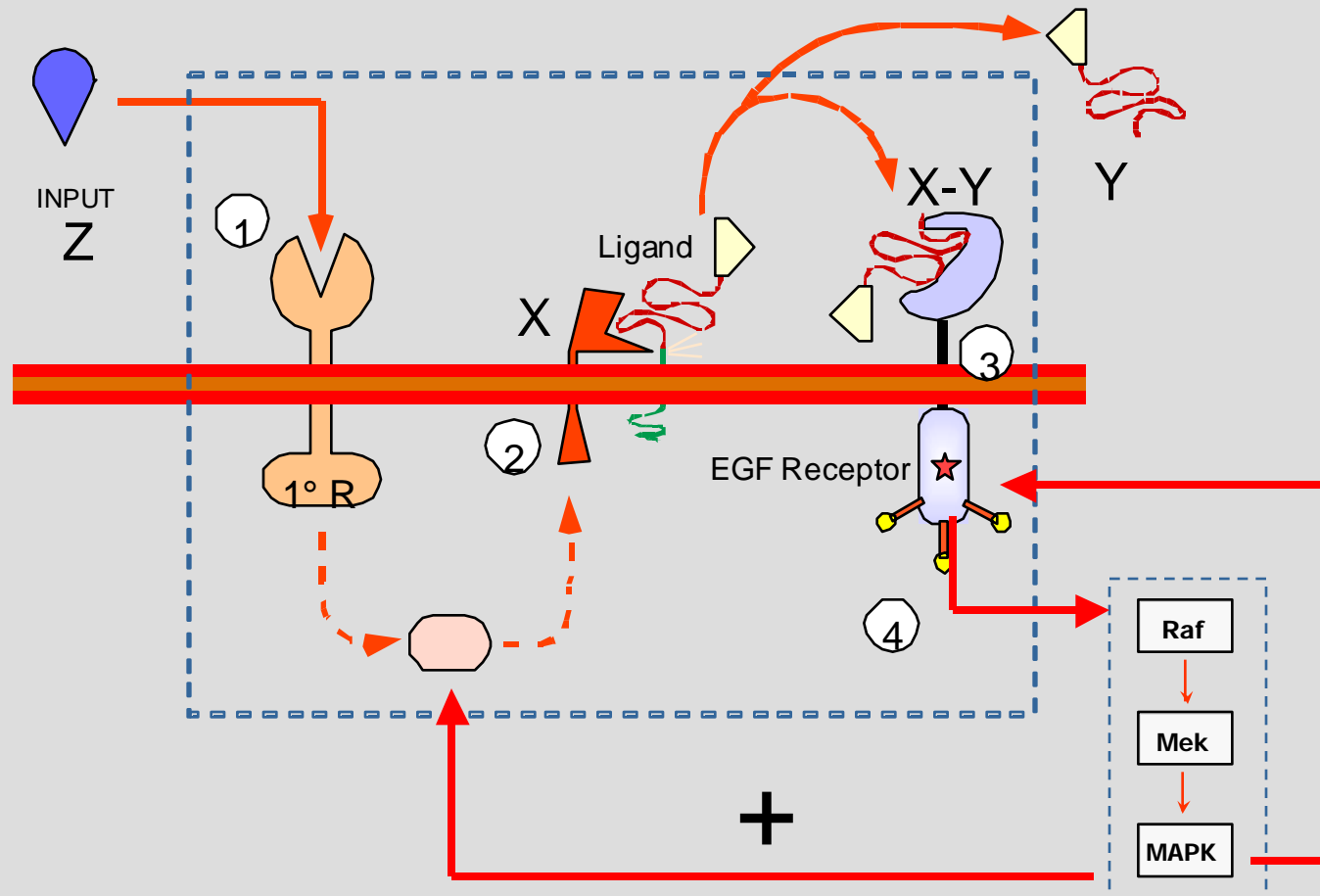
TNF α Stimulates Two Waves of MAPK Activation



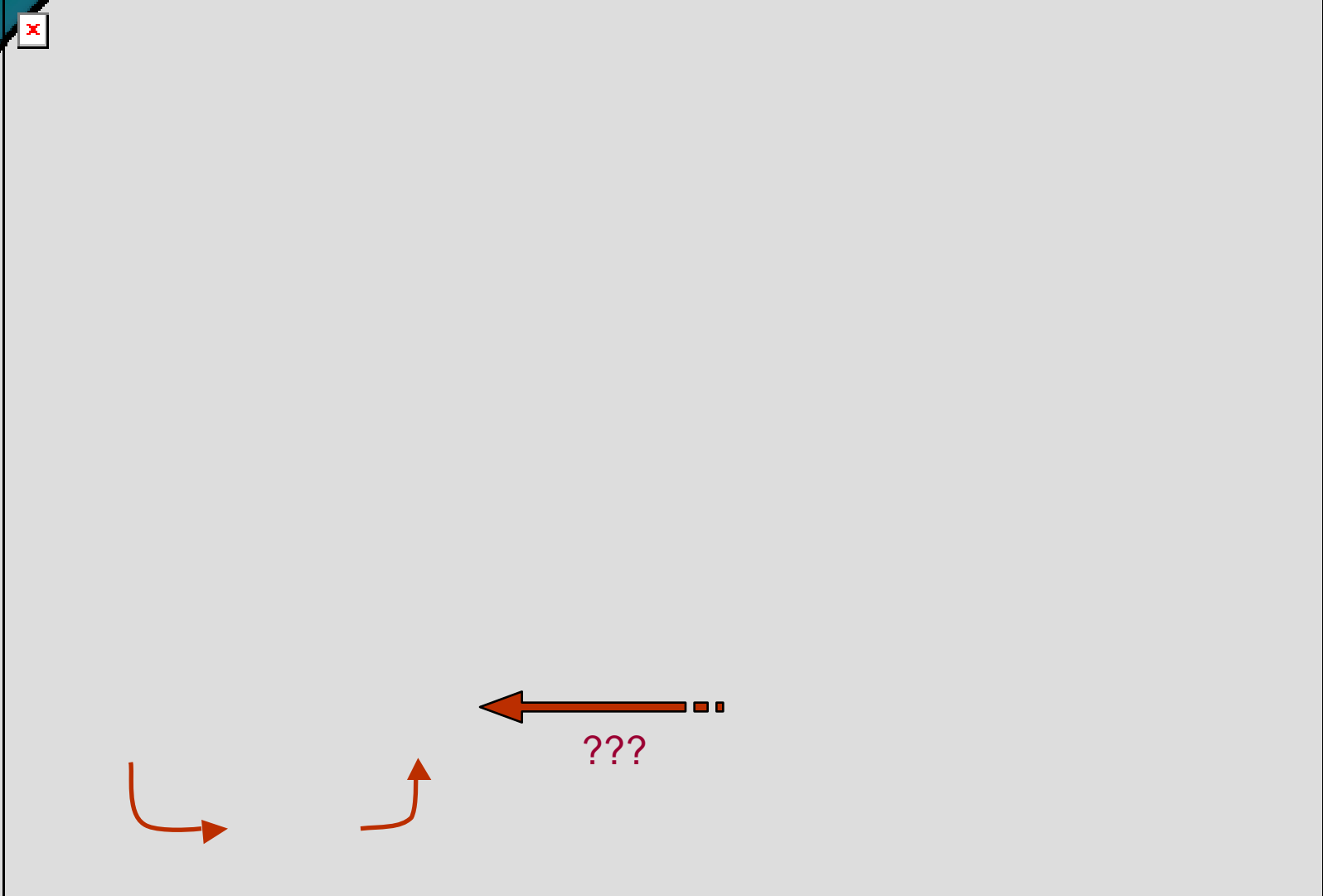
Shedding Response is Graded



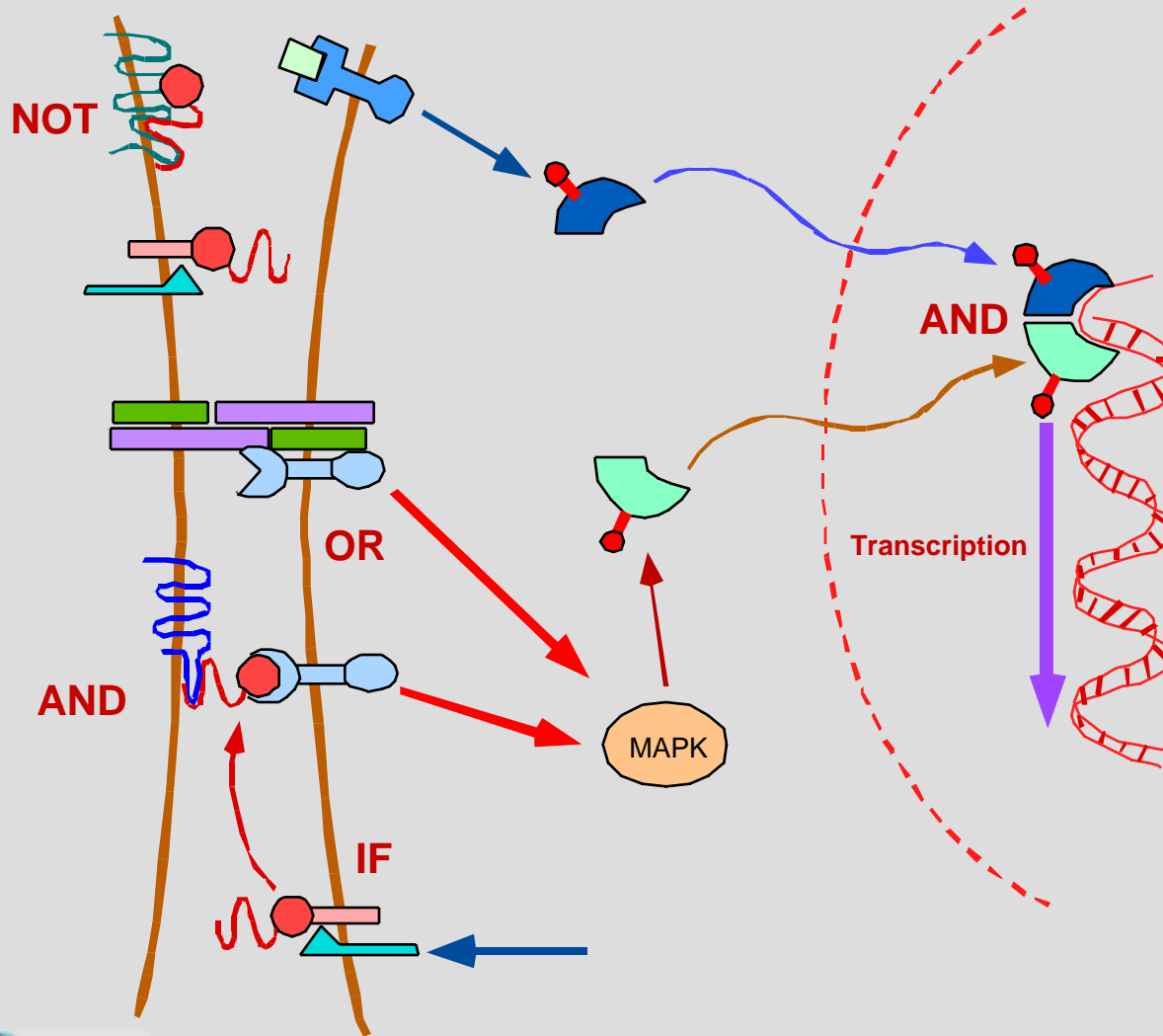
Autocrine Signaling as a Control Circuit

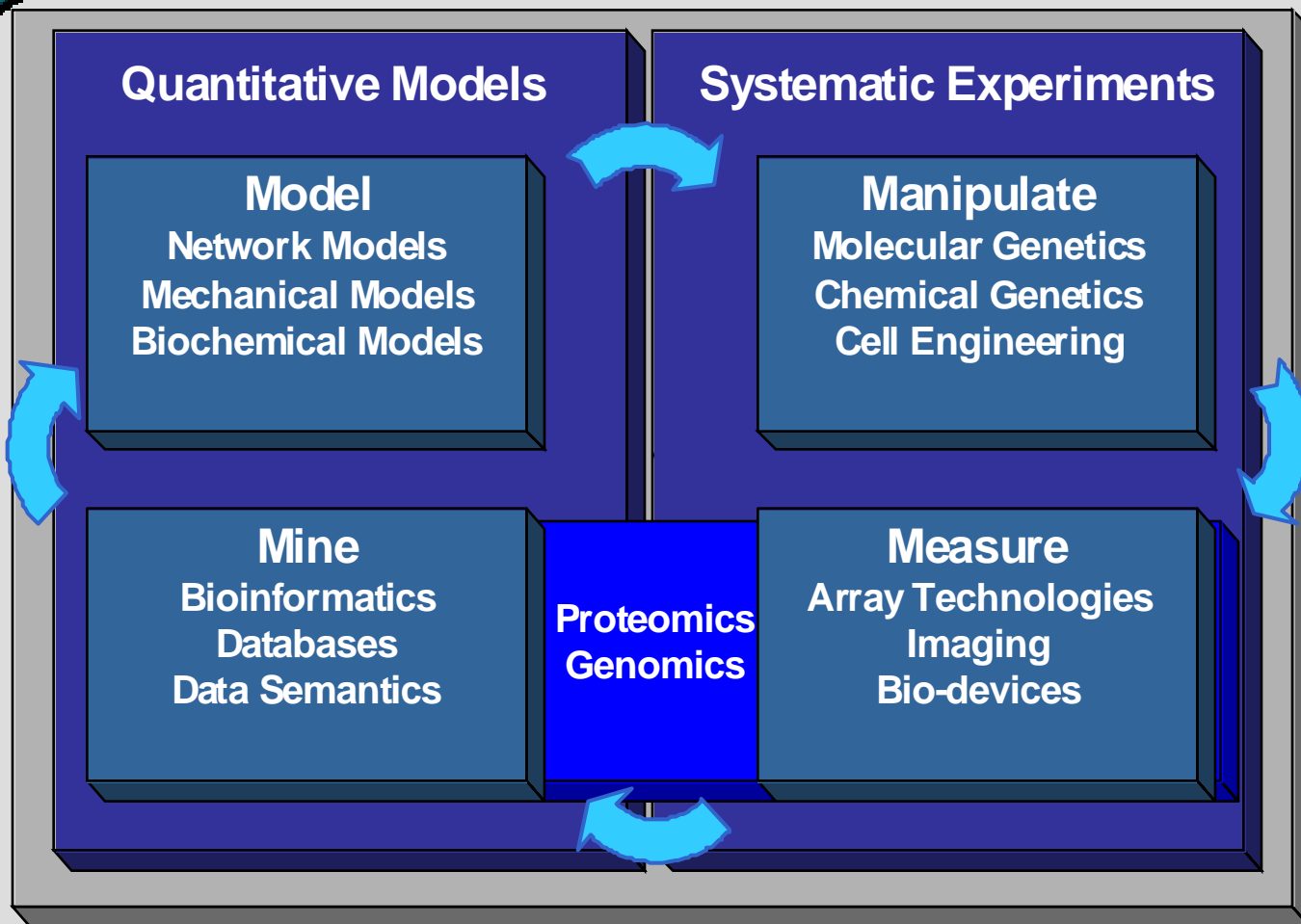


Interrogative Signaling



Information Processing at the Cell Surface





Computation:

- elucidate hypotheses (*mining*)
- facilitate predictions (*modeling*)

Systematic experimentation:

- quantitative
- multi-variable

Acknowledgements

- ▶ Lee Opresko
 - ▶ Patrick Burke
 - ▶ Will Chrisler
 - ▶ Brian Thrall
 - ▶ Maggie Wolfe
-
- ▶ Stas Shvartsman
 - ▶ Doug Lauffenburger
 - ▶ Trey Ideker

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